

SPATIAL AND TEMPORAL VARIABILITY OF SEA SURFACE  
TEMPERATURE AND FISHERIES DISTRIBUTION WITH THE NORTH  
ATLANTIC OSCILLATION

By

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## **Abstract**

Increasing evidence supports relationships between fisheries distribution and climate variability. The main driver of climate variability in the North Atlantic Ocean is the North Atlantic Oscillation (NAO). Fisheries distribution is influenced by sea surface temperature (SST), which displays a dynamic relationship with the NAO. To assess these relationships, we conducted a spatial and temporal analysis of SST, fisheries distribution, and the NAO from 1986 to 2008 in the Northwest Atlantic and Gulf of Mexico. We conducted a pixel-level linear regression analysis with the USGS Curve Fit tool in ArcMap to examine the spatial patterns of correlation coefficients and goodness of fit between monthly SST and monthly NAO index. We identified five regions in the Northwest Atlantic, and two regions in the Gulf of Mexico, where coefficients demonstrated relatively significant correlation between SST and the NAO. These regions were consistent with local ocean circulation patterns. To assess the relationship between the NAO and fisheries distribution in the identified correlation regions, we calculated linear regressions between tuna and swordfish catches and effort distribution with the NAO as the explanatory variable. Our results suggest that our linear model with the NAO as the single explanatory variable was too simplistic to explain fisheries catch and distribution variability. Further study using different models and explanatory variables may elucidate significant relationships between SST, fisheries distribution, and the NAO. Trends between fisheries and the NAO may provide insight into future effects of climate change on fish stocks with implications for fisheries management.

## **1. Introduction**

Increasing evidence supports relationships between sea surface temperature, fisheries distribution, and climate variability indices, such as the North Atlantic Oscillation (NAO) (Sparrevohn et al., 2013; Salinger et al., 2013; Lehodey et al., 2006). The NAO is a variation in sea

level pressure between the Arctic and subtropics of the North Atlantic Ocean accounting for one third of the total variance in monthly mean sea level pressure (Salinger, 2013). These pressure oscillations are associated with changes in wind speed and direction, which dictate heat and moisture transport and the resulting weather patterns, sea ice cover, and sea surface temperature of the North Atlantic (Hurrell et al., 2003). Evidence suggests a dynamic relationship between the NAO and sea surface temperature; one does not simply cause the other (Wang et al., 2004).

Regardless, it is generally understood that sea surface temperature is a critical determinant of population range for marine species (Bertness et al., 2014). Globally, marine species are expected to shift poleward in response to warming temperatures (Parmesan and Yohe, 2003). Locally however, additional physical parameters, such as currents, habitat types, and depth will affect the magnitude and direction of individual population shifts (Bertness et al., 2014; Pinsky et al., 2013). While SST and the NAO are not the only physical factors that influence fisheries distribution, understanding past relationships may help predict future climate change effects (Salinger et al., 2013, Sparrevohn et al., 2013, Lehodey et al., 2006).

Climate-induced fisheries movements have already been implicated in jurisdictional disputes, and projections show that climate change may trigger a global redistribution of fisheries catch potential (Pinsky et al., 2013; Cheung et al., 2011; Cheung et al., 2010). As a result, there is growing support for the application of adaptable approaches to traditional fisheries management schemes (Pinsky et al., 2013; Salinger, 2013; Cheung et al., 2010; Mueter and Litzow, 2008).

The purpose of this study was to examine regional responses to climate variability in the Northwest Atlantic and Gulf of Mexico. To do this, we used pixel-level regression analysis to examine spatial and temporal variability of relationships between SST and the NAO. We identified recurring correlation regions based on the resulting spatial patterns, and then analyzed the relationships between tuna and swordfish fisheries catch and distribution with the NAO in the



identified regions. Our motivation for this study is detailed in the following background section. Our methods and results are explained in sections three and four and the implications of our results are discussed in sections five and six.

## **2. Background**

Actions to prevent the overharvest of fisheries, such as quotas, are complicated by limitations in science and enforcement. Motility of aquatic species, lack of accessibility, and uncertainty of ecological models affect scientific abilities to produce accurate stock assessments used to determine quotas (Jones et al., 2012; Jorgensen et al., 2012). Fish do not adhere to political boundaries, and highly migratory species (HMS), such as tuna and swordfish, range across ocean basins. Challenges of administering quotas for HMS are augmented on the international level where there is no governing authority to enforce regulations, and negotiating nations possess diverse cultural values (Miller, 2007). These challenges will most likely persist into the foreseeable future, however, changing climate conditions may present large-scale regulatory conflicts with increased frequency.

Assessment of the current total ecology (Orbach, 2009) of North Atlantic HMS outlines the policy issues of managing HMS in a changing climate system. This background section provides an overview of the biophysical, human, and institutional ecologies of North Atlantic HMS, while focusing specifically on implications for Atlantic tuna and swordfish in the context of climate variability.

### **2.1 Policy problem**

Fish distribution changes across international boundaries are cause for concern, potentially limiting or increasing a nation's prior access to a fishery, threatening resource security and livelihoods, and fueling political tensions (Salinger et al, 2013; Lehodey et al., 2006). For example, in response to an influx of herring attributed to climate change and higher catch rates, the Faroe

Islands self-imposed a quota more than triple the quota allotted to them by an existing regional agreement. This unilateral action prompted the European Union to impose economic sanctions on Faroe Islands fisheries (Keane, 2013; Thaler, 2013).

Scientific data is often requested to guide policy decisions and agreements, yet climate and fisheries models are limited in predictive capabilities (Jones et al., 2012; Jorgensen et al., 2012). Despite scientific uncertainty, domestic and international institutions are tasked with managing these valuable resources. Conflicts inevitably arise between stakeholders with varying interests and climate change could produce biophysical impacts unfamiliar in spatial-temporal scale (Cheung et al, 2011; Miller, 2007). The effectiveness of management schemes currently in place is crucial to cope with impacts on economic and political stability.

## **2.2 Biophysical ecology**

The biophysical ecology of this section is broken up into three parts: ecological factors and characteristics of highly migratory species, physical and oceanographic factors of the North Atlantic Oscillation, and the relationship between the two.

### *The Ecology of Highly Migratory Species:*

Atlantic highly migratory species managed by the Atlantic Highly Migratory Species Management Division of the National Marine Fisheries Service, include pelagic tunas, sharks, swordfish and billfish. Although grouped together for management purposes, HMS have different life histories with a variety of migration and foraging behaviors. Some species, such as bluefin tuna, migrate along established routes, and others follow less regular paths (Block et al. 2005, Sibert and Hampton, 2003).

The open ocean is a harsh environment, without the reliable productivity of coral reefs and seagrass beds. In an environment with few physical barriers, and fluctuating oceanographic conditions, both tuna and swordfish migrate and forage along routes that provide them with optimal

habitats for their life stages (Miller, 2007; Block et al., 2001). HMS follow prey to places of high productivity, which tend to be frontal regions with upwelling and mixing thermoclines. Upwelling increases the availability of nutrients, which facilitate primary productivity. High productivity attracts consumers, small fish and cephalopods, which are prey for large, highly migratory predators (Miller, 2007; Potier et al., 2007; Stillwell and Kohler, 1985).

Size, speed, and high metabolism require HMS to constantly forage for food (Miller, 2007). As a result, highly migratory species tend to be generalists, feeding on a diversity of prey species. As generalists, they consume the most readily available prey species, which is beneficial for quantity as well as for competition. For example, in the North Atlantic, swordfish primarily consume cephalopods, but if other prey items, such as butterfish, gadids and mackerel become available, an increased amount of these animals are found in their diet (Stillwell and Kohler, 1985).

Differentiation of foraging behavior between HMS reduces competition for prey. For example, although swordfish and tuna target similar prey, swordfish forage in the mesopelagic zone, deeper than the yellowfin tuna, which forages in the epipelagic (Potier et. al, 2007). Comparison of stomach content analysis in the Indian Ocean found that swordfish and yellowfin tuna fed on the same species of cephalopod, however the tuna fed on epipelagic juveniles, and the swordfish fed on mesopelagic adults (Potier et. al, 2007).

#### *The North Atlantic Oscillation (NAO):*

In the Pacific Ocean, El Nino and the Southern Oscillation (ENSO) is a fairly well studied and commonly known system. ENSO is characterized by patterns of variability in the surface ocean and atmosphere. El Nino (unusual warming of the Eastern Tropical Pacific) and La Nina (the opposite-unusual cooling) affect rainfall and weather as well as sea level, thermoclines, and upwelling (Stenseth et al., 2003). Changes in temperature, thermoclines, and upwelling impact fish populations

and fisheries, such as anchovies and sardines in Peru and Chile, as well as tropical tuna species (Lehodey et al., 2006).

The effects of the North Atlantic Oscillation are comparatively less studied. The NAO shifts over irregular time scales and its effects are most noticeable during winter months. During the positive phase, strong subtropical high pressure near the Azores and strong polar low pressure near Iceland produce warmer temperatures and increased precipitation in northern Europe and the southeastern US, and colder and dryer weather in Canada and Greenland (Hurrell et al., 2003; Lamb and Pepler, 1987). Positive phases also bring warmer weather and warmer sea surface temperatures to the Barents Sea region, as well as colder weather and sea surface temperatures, in the Labrador Sea (Lehodey et al., 2006). During the negative phase, weak subtropical high pressure near the Azores and weak low pressure near Iceland produce the opposite effects (Hurrell et al., 2003; Lamb and Pepler, 1987).

Similar to ENSO events, the shifting phases of the NAO affect oceanographic parameters such as temperature and thermoclines (Stenseth et al., 2003). For example, northwest Atlantic sea surface temperature anomalies are below average during positive phases and above average during negative phases. (Salinger, 2013).

#### *Highly Migratory Fish Species and the NAO:*

The phases of the NAO affect oceanographic variables, ultimately influencing fish populations (Salinger, 2013; Stenseth et al., 2003). The effects are documented most well documented with cod stocks (Lehodey et al., 2006). While not considered highly migratory, the effects of weather patterns on cod are well studied, unlike that of highly migratory species, which tend to be data-poor.

In the 1990s, the NAO displayed a strong positive phase, resulting in high temperatures in the North Sea, which had an unfortunate effect on cod stocks. The change in temperature resulted

in a decrease in the quality and quantity of larval cod prey species, such as the copepod *Calannus finmarchicus*. With less food available, cod larvae did not have the resources to flourish (Lehodey et al., 2006). In warmer temperatures, the metabolic rate of ectothermic species like cod increase, but without food to support this high metabolic rate, survival drops considerably (Lehodey et al., 2006).

Atlantic Bluefin tuna are also sensitive to temperature variability (Block et al., 2001). In the Gulf of Mexico, a breeding ground for Bluefin, they prefer frontal zones and cooler sea surface temperature. Cooler temperature befits their large body size. These cooler regions in the Gulf tend to be produced by productive upwelling, thus improving the availability for food and survival for larvae (Teo and Block, 2010).

As previously mentioned, prey species of large open-ocean apex predators tend to congregate around areas with thermocline mixing—areas with upwelling or fronts. Swordfish, for example, show a strong preference for decaying fronts. This is likely due to the biomass of prey species that accumulate because of upwelling (Bigelow et. al, 1999). In different phases of the NAO, the North Atlantic will alternatively experience warm and wet or cool and dry temperatures, and fronts and storms will move accordingly, theoretically followed by primary productivity, prey species, and open ocean predators (Salinger, 2013).

Changes in weather patterns caused by the flux of NAO transition events influence sea surface temperatures. As such, the NAO has simulation potential for variations in sea-surface temperatures associated with climate change (Sparrevohn et al., 2013; Wang et al., 2004). Correlation of past changes in fish distribution with an index of the NAO events may help predict future changes in fish distribution correlated with climate change (Salinger, 2013; Stenseth et al. 2013). Due to the wide, open ocean range of HMS, they are likely to experience broad changes in oceanographic variables throughout their territory. Thus, both anomalies caused by the NAO – warm and wet or cool and dry – can prove as useful simulations.

## 2.3 Human ecology

Humans value HMS for the economic and intrinsic benefits they provide. Reliance on North Atlantic fisheries for subsistence and economic gain was essential to the success of early settlers and the foundation of the American colonies. By the mid-1900s technological improvements and industrialization of fishing fleets increased catch potential and access to the high seas for longer periods of time (Cooke, 2013).

This industrial growth increased pressure on fish stocks and diversified stakeholders. The availability of highly migratory species increased, and access to consumers living further inland expanded. Local, small scale fishing operations with direct fisher to consumer interactions gave way to longer, more complicated supply chains, involving fishers, dealers, processors, whole-sellers, stores, restaurants, and consumers (Cooke, 2013). By the late 1900s, effects of increased pressure were evident from declining catch rates (Myers and Worm, 2003). Environmental interest groups emerged, concerned with conservation for the intrinsic value of fishes as opposed to economic value alone. While the values of commercial, recreational, and environmental stakeholders are not mutually exclusive, their interests and resulting policy implications can be described separately.

### *Commercial Interests:*

The decline of fish stocks as a result of industrialization prompted more regulation of both US commercial and recreational fisheries. Increased regulation made entering the industry and complying with these rules more complicated and particularly difficult for US commercial fishermen (Cooke, 2013). For example, in response to declining swordfish stocks in the 1990s, international quotas were reduced, areas were closed to longlining, and harvest of swordfish for American commercial fisheries was cut drastically (Pickrell, 2002; Prewitt, 1998). Today, the North Atlantic swordfish fishery is a limited access fishery and no new permits are issued. New entrants must find current permit holders to give or sell their limited access permits. The type of permit depends on

retention rate, gear type, and permit holders must also comply with protected species regulations (NOAA HMS Division, 2013).

Although industrial vessels comprise only four percent of the North American fleet, restrictive barriers tend to favor these larger entities over small-scale operators with less capital (FAO, 2010; Cooke, 2013). One emerging trend small-scale commercial fishermen utilize to rectify challenges of entry barriers and regulation is by establishing community-supported fisheries (CSFs). Market and non-market benefits of CSFs include risk sharing, regulatory support, promotion of underutilized species, and low-impact methods (Brinson et. al, 2011).

While HMS are not often targeted by CSFs, the CSF model demonstrates the adaptability of commercial fishers, in creating new markets that supply the demand for sustainable products by ecologically conscious consumers. This adaptability appears to be mutually beneficial, providing fishers premium prices for their catch by willing participants. It illustrates the multi-faceted values of commercial industry stakeholders. Fishers may strive for economic gain, but also benefit from long-term stability and sustainability.

This presents a paradox for commercial interests in the management realm. Too much management places a burden on fishers—a threat to livelihood and an affront to the notion of the freedom of the seas. However, weak management and unrestricted access does not protect against overharvesting—also a threat to livelihood, and an inevitable tragedy of the commons (Hardin, 1968). For example, restrictions of the swordfish recovery plan of the 90s are deemed successful at rebuilding North Atlantic swordfish stocks, yet recovery plans are often met with resistance fueled by mistrust in scientific agencies (NOAA, 2012; Hartley, 2008)

Commercial interests are represented by a growing number of trade associations. The National Fisheries Institute is a non-profit trade association that represents all levels of the commercial supply chain. Like most American trade associations, they promote seafood awareness

and sustainability to protect the vitality of the American commercial fishing industry (NFI, 2013). While these interest overlap with other stakeholders, in practice, commercial interests are demonstrably different. For example, while recreational fishermen and environmentalist consumers generally supported the consumer swordfish boycott of the 90s, the National Fisheries Institute felt it erroneous in light of regulations already instituted by the recovery plan (Prewitt, 1998).

Interest groups such as the Atlantic Bluefin Tuna Association (ABTA) represent variation within the commercial fishing industry itself. The ABTA represents traditional commercial fishing techniques such as hook and line and harpoon gear, as well as recreational fishers and charter operations (ABTA, 2013). U.S. commercial harvest of most tuna species and swordfish is done predominantly by longline. Atlantic Bluefin are harvested by purse seines and hand gear, with restrictions on incidental catch by longlines (NOAA FishWatch). The ABTA takes an active stance to protect traditional and recreational fishers' access to the tuna fishery, by promoting quota limits on commercial longliners (ABTA, 2013).

#### *Recreational Interests:*

In contrast to commercial or subsistence fishing, recreational fishing is often considered a leisure activity—not reliant on HMS for survival. However, the recreational fishing industry has a large impact in the U.S. economy. According to the American Sportfishing Association (ASA)—a recreational fishing trade association—it is estimated that recreational fishing has “...a total annual economic impact of \$115 billion...supports more than 828,000 jobs and generates \$35 billion in wages and \$15 billion in federal and state taxes” (Williamson, 2013).

As illustrated by the stance of the ABTA, commercial and recreational fishermen essentially compete for access to HMS. According to the ASA website, their members “...have different concerns varying from the federal manufacturers' excise tax, counterfeiting, marketing and supply



line changes, participation in the sport and keeping our nation's waters open, clean and abundant with fish and ASA represents all their interests" (ASA, 2012).

Taxes on equipment and fishing licenses generate over \$1 billion for fisheries conservation and management (Williamson, 2013). However, the environmental impact of the recreational industry is often over-looked in comparison to commercial fisheries, and there are records of fisheries collapsing due to exploitation by recreational fishers (Wolf-Christian et. al 2006). Although recreational fisheries are subject to their own fees, permits, and regulations, the true impact is underestimated since the number of recreational fishers is harder to monitor than commercial fishers.

The large size of HMS including swordfish and tuna make them popular targets of sport fishing. According to a survey of anglers conducted by NOAA, a majority of recreational fishers believe in supporting long-term sustainability of fisheries, understand the effects of overfishing on the ecosystem, and the importance of management (NOAA, 2013). However, targeting for size and removing the largest individuals can cause population effects including a decrease in the average size of the species. Although commercial fisheries have a greater share of total allowable catch, any additional pressure by recreational fishery size targeting can be particularly detrimental for slow growing apex predators, such as sharks (Wolf-Christian et. al 2006). These effects prompt maximum size limits in addition to minimum size requirements for the retention of some species (NOAA FishWatch).

#### *Environmental Interests:*

The interests of HMS stakeholders are not mutually exclusive, and environmental interests in fisheries management exist on a broad continuum. Commercial and recreational industries have vested interests in preventing overfishing, but access to the fishery is a priority and the notion of sustainability implies an ability to continue harvesting. Thus, while recreational and commercial

stakeholders have environmental interests, there are stakeholders who promote sustainability and conservation of HMS for their intrinsic value alone.

In this consideration, intrinsic value is not tied to personal economic gain. However, humans still place a *value* on the existence of HMS. This is represented by their willingness to pay for conservation efforts. Similarly, consumers and restaurateurs express their value of HMS with their purchasing power and what they choose to serve on the menu. The swordfish boycott of the 90s was instigated by environmental groups and high-end restaurant chefs, which exposed their potential influence in the policy arena (Prewitt, 1998).

People value the existence of HMS for a variety of reasons. Some value biodiversity and the role HMS play in the ecosystem. SeaWeb and the Natural Resources Defense Council were the two groups behind the aforementioned swordfish boycott (Prewitt, 1998). While philosophical arguments for conservation are beyond the scope of this paper, interest groups such as these represent general environmental interests. These advocacy groups commonly employ lawyers, scientists, and managers to organize public support for environmental campaigns, hold government agencies accountable for enforcing environmental regulation, and oppose harmful practices. Many environmental organizations recognize the diversity of their members by promoting sustainable practices beneficial to both the environment and fishing industry. For example, the Environmental Defense Fund (EDF) was instrumental in the implementation of catch shares (EDF, 2013). Similarly, the Billfish Foundation (TBF) emphasizes the use of science to inform fisheries policy decisions to promote conservation without severely obstructing access of recreational fishers (TBF, 2013).

The multi-disciplinary nature of interest groups reflects the diversity of stakeholders invested in the management of highly migratory species. As stakeholders diversified, the boundaries between seemingly opposing interests dissipated. Commercial fishers may also be recreational fishers that

value both conservation and harvest. Environmentalists may consume HMS, but support restrictive quotas. While the idea of sustainability manifests differently, stakeholders share a common interest. The potential volatility of climate change effects may hamper the discord between these groups, or be quelled by their cooperation.

## **2.4 Institutional ecology**

The migratory nature of highly migratory species presents challenges beyond the realm of domestic and regional institutions that govern other fisheries. Without physical bounds, HMS are exposed to a variety of habitats, as they move from one food source to another, and through life history stages. However, human institutions attempt to delineate jurisdictional boundaries. These boundaries are drawn invisibly over stretches of ocean. Unfortunately, fish and have little regard for governance. Highly migratory species frequently cross boundaries of states, regions of fisheries management councils in the United States, and exclusive economic zones (EEZs) of nations. This creates problems in terms of stock assessments, overfishing and bycatch; it is difficult to monitor species that cross boundaries without communication and cooperation (Miller, 2007). In this section, the ecology of highly migratory species will be broken down by institution.

### *Highly migratory species in the United States: HMS Management Division:*

Federal fisheries, which take place in the US Exclusive Economic Zone and beyond state waters, are governed Fisheries Management Councils. These councils control one of eight regions of US fisheries in federal waters-three to two hundred nautical miles from shore. Highly Migratory species cross between and outside of these councils' jurisdictions, making them difficult to govern. In 1990, the Magnusson Stevens Act was amended to separate highly migratory fish species from other species fished in federal waters. Authority over highly migratory species was given to the Secretary of Commerce. The Secretary further delegates this authority to the National Marine Fisheries Service, which created the Highly Migratory Species (HMS) Management Division. The

HMS management division is charged to manage and regulate the fishing of highly migratory species in the US (NOAA, 2014).

Though highly migratory species share many similarities, each species occupies a slightly different niche and commercial value differs. As a result, the HMS management division develops different fishery management plans for each species, with separate permits and regulations for commercial and recreational fisheries. The Division supervises fisheries under their jurisdiction in order to gather data, implement, and enforce quotas for both recreational and commercial sectors (NOAA, 2014).

*International Commission for Conservation of Atlantic Tuna:*

Particularly valuable species like Bluefin tuna (*Thunnus thynnus*) can easily become overexploited if nations do not work together. In 1966 the US signed the International Commission for Conservation of Atlantic Tuna (ICCAT). ICCAT is an international agreement formed in order to manage and conserve tuna and other large, highly migratory apex predators. Its primary focus is on stock abundance, as well as bycatch and illegal, unreported, and unregulated fishing. ICCAT releases recommendations based on stock assessments in order to maintain tuna and other highly migratory species populations at levels of sustainable harvest (ICCAT, 2009).

Auxiliary bodies draft and present resolutions and recommendations to the commission, which are later adopted. ICCAT was signed into US national law in 1975 with the Atlantic Tuna Conservation Act, which places US commissioners in the position of an auxiliary body. US commissioners can create working groups focused on individual species offer recommendations to ICCAT for adoption (“16 USC Chapter 16A”, 1992).

*United Nations Fish Stocks Agreement:*

In the US, domestic Regional Fishery Management Councils can jointly manage stocks of species that migrate through multiple jurisdictions. States can also jointly manage coastal migratory

species. In 1995, the United Nations Fish Stocks Agreement was initiated to address the need for international cooperation in governing HMS that migrate through multiple EEZs. This agreement supports efforts to establish Regional Fishery Management Organizations (RFMOs) (Miller, 2007). Numerous RFMOs, including ICCAT, have been established around the globe and are diverse in terms of their member nations and in the areas and species that they govern.

#### *Treaty with Canada: The Albacore Tuna Treaty:*

The 1976 Magnusson-Stevens Act states that Albacore Tuna can be fished inside another country's EEZ, and that any arrest of US fishing vessels may result in an embargo. In 1979, a US vessel fishing for Albacore in Canadian waters in the Pacific was seized and the fishermen arrested (Rugman et. al, 1999). This resulted in an embargo on tuna from Canada. Three years later, the Albacore Tuna Treaty was signed. It states that US fishermen can indeed fish for Albacore the Canadian Exclusive Economic Zone, and Canadian fishermen can fish for Albacore in the US Exclusive Economic Zone (Rugman et. al, 1999). It is specific to Albacore tuna, and while the whole affair took place in the Pacific, rather than in the Atlantic, it is relevant to the management of other HMS.

There are many international agreements that involve participation of two or more nations for the conservation and management of HMS (Miller, 2007). Generally, a signatory party to an international treaty must incorporate the agreed upon regulations into their own domestic policies. Each nation then enforces their own laws in their EEZ. This can be problematic—enabling a lack of enforcement and accountability (Miller, 2007).

### **3. Methods**

#### **3.1 Data acquisition and extent**

Our study focused on two regions in the Northwest Atlantic Ocean and the Gulf of Mexico, and we acquired three sets of data: satellite sea surface temperature rasters, monthly NAO index,

and Atlantic Highly Migratory Species (HMS) Division longline data. We determined the extent of our study region in the Northwest Atlantic Ocean based on the extent of the available tuna and swordfish fishery data points. This area was between 15-70°N latitude and 45-100°W longitude. In addition, we analyzed the entire Gulf of Mexico between 17.89-30.77°N latitude and 97.87-30.77°W longitude.

We downloaded mean, monthly, nighttime SST rasters using the Marine Geospatial Ecology Tool (MGET) “create climatological rasters for AVHRR Pathfinder V5.2 SST” from 1986 to 2008 for the NW Atlantic extent described above (273 rasters total; October, November, and December rasters from 1994 were unavailable). We masked the Gulf of Mexico extent from those downloaded raster surfaces.

We retrieved the monthly NAO index from the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center. The index is calculated using Rotated Principle Component analysis and applied to monthly-standardized 500-mb height anomalies (Barnston and Livezey, 1987).

Finally, we obtained North Atlantic longline catch and effort data for tuna and swordfish from fisher reported logbooks (NMFS Atlantic HMS Division) from 1992-2008. Tuna species included Bluefin, Yellowfin, Bigeye, and Albacore.

### **3.2 Data preparation**

We conducted a multi-step process of data preparation in ArcGIS and Python (Appendix C) prior to pixel-level regression analysis with USGS Curve Fit, which is explained later. This multi-step process involved interpolation of SST rasters, calculating SST Z-score rasters, and SST Z-score anomalies for both study regions. We also prepared point shapefiles of the tuna and swordfish longline data.

First, we converted the monthly SST rasters to point shapefiles and interpolated them via Inverse Distance Weighted (IDW) to fill raster cells that had no data. This was necessary prior to analysis with Curve Fit, which will not accept no data values. A single no data value for a pixel in the input raster dataset results in a no data value for that pixel in the output raster (Figure 1). We averaged the interpolated SST raster surfaces by month across all years to produce a data set consisting of twelve rasters. Each average served as a monthly baseline for the typical condition of SST in the study region.

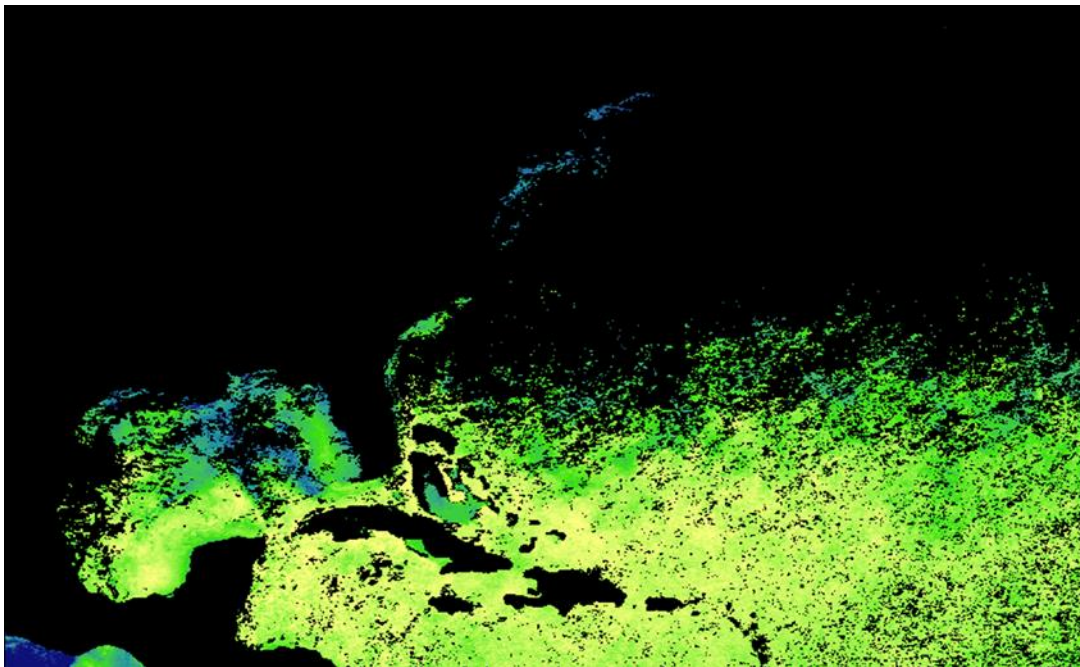


Figure 1. Resulting raster image of Curve Fit without interpolation of input rasters. Black pixels represent regressions that had no data for at least one pixel in the input raster dataset. This raster is clearly inadequate for analysis. Interpolation of SST rasters filled pixels with no data and produced adequate rasters.

To standardize sea surface temperature variability and detect anomalies, we calculated SST Z-score raster surfaces for each month, as well as each monthly baseline raster. We then calculated the difference between each monthly SST Z-score raster and the corresponding monthly baseline raster. We used these SST anomaly raster surfaces as the input datasets for regression analysis with the NAO.

We repeated the process of standardizing SST variability and detecting SST anomalies (averaging monthly SST, calculating SST Z-score, and SST Z-score difference rasters) for the Gulf of Mexico study region to refine analysis at a smaller spatial scale. This removed the influence of northern latitude SST variability on the Gulf of Mexico, where we expected consistently warmer temperatures.

Finally, we created point shapefiles of the fisher reported logbook data based on the recorded latitude and longitude of set longlines (Figure 2). These points were used in the fisheries distribution analysis described in section 3.3.2.

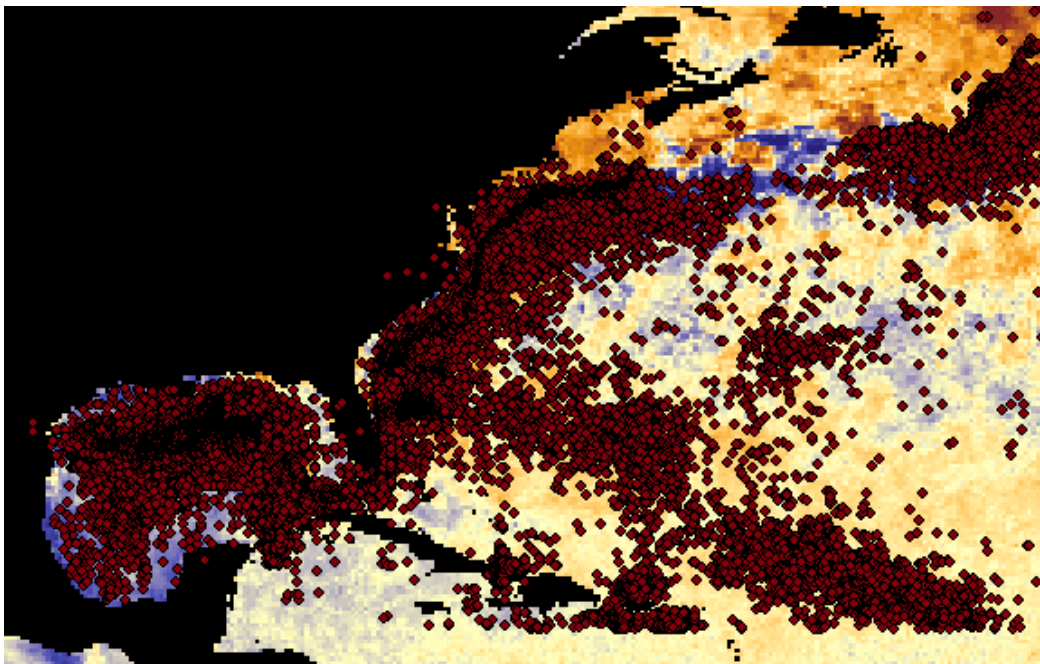


Figure 2. Tuna and swordfish longline fishery data points. There were few data points in the Gulf of Maine, which excluded it from further analysis. Note the clustering of data points in the Sargasso Sea.

### 3.3 Spatial and temporal analysis

#### 3.3.1 SST and the NAO

Spatial and temporal analysis of SST and the NAO involved the relatively new USGS Curve Fit tool (De Jager and Fox, 2013), and visual assessment of spatial and temporal patterns between concurrent and time-lagged regressions of SST and the NAO.



We used the USGS Curve Fit tool (Figure 3) to assess the relationship between SST anomalies (henceforth referred to as simply SST) and the NAO, with the NAO as the explanatory variable. This method allows for the detection of spatial variability across all years by allowing each pixel to retain its spatial and temporal context (De Jager and Fox, 2013); each pixel within an output raster is the result of the linear regression of values at that pixel location across all years (1986-2008) in the monthly data set.

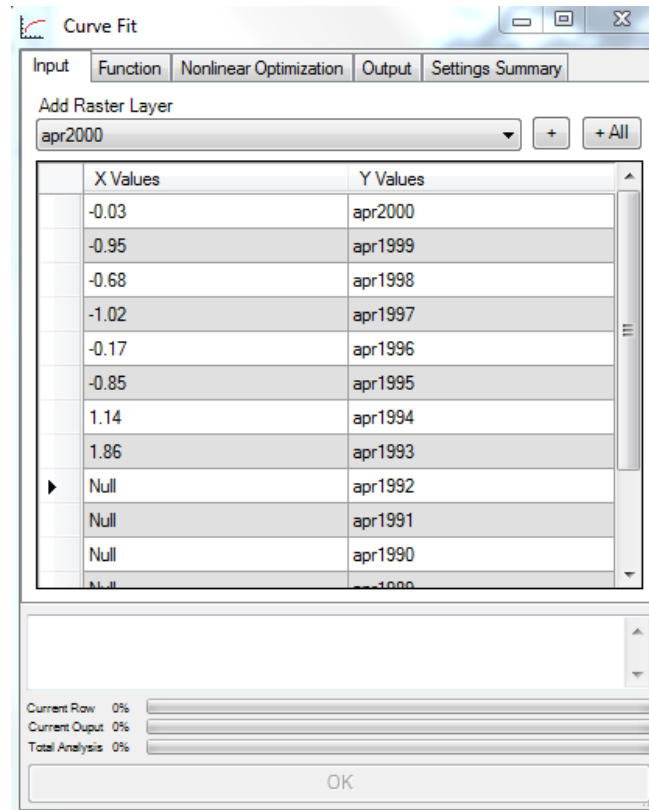


Figure 3. USGS Curve Fit available as an extension in ArcMap. The user inputs raster datasets (SST) and explanatory variable values (NAO index) (De Jager and Fox, 2013).

We parameterized Curve Fit to return  $R^2$ , p-value, and coefficient raster surfaces for each linear regression between monthly SST dataset (y variables) and monthly NAO index (x variables). We used  $R^2$  and p-value to assess goodness of fit ( $R^2$  measured correlation; p-value measured confidence level), and coefficients to identify magnitude and direction of the relationships.

Studies suggest that seasonal time-lags may play a role in the dynamic relationship between SST and the NAO (Wang et al., 2004). We calculated two sets of regressions, concurrent and time-lagged, for each study period. The time-lagged regressions included a lag of six months between monthly SST and monthly NAO, with the NAO preceding SST (e.g. January 2008 SST with July 2007 NAO). We compared the results of concurrent regressions with the time-lagged regressions in our visual analysis for spatial and temporal patterns.

We visually assessed the output raster surfaces of both concurrent and time-lagged regressions to identify recurring regions of relatively significant correlation within the study areas. First, we located the overall pattern of positive and negative correlation regions in each of the output coefficient rasters. Then we referenced the corresponding  $R^2$  and p-value raster surfaces to assess explained variance and significance of the pixel-level linear regressions in each correlation region. Areas with habitual correlation significance were identified as regions for the following fisheries distribution analysis.

### **3.3.2 Fisheries distribution and the NAO**

We assessed the relationships between tuna and swordfish catch and effort distributions with the NAO within the correlation regions identified in the previous section. We isolated longline fishery data points by region in ArcMap, and calculated linear regression models using R statistical software with the NAO as the explanatory variable (Appendix B).

We analyzed tuna (Bluefin, Yellowfin, Bigeye, and Albacore) and swordfish catches were analyzed separately. Catch represented the number of individual fish caught at each longline data point, which was where the longline was originally set. We assessed fisheries distribution by both latitude and longitude. We used the  $R^2$  and p-value from the output statistical summaries to determine variance explained and significance of our models.

## 4. Results

### 4.1 Spatial and temporal analysis - SST and the NAO

Based on regression coefficient,  $R^2$ , and p-value output raster surfaces (Figure 5; Appendix A.1; A.2), we identified 5 correlation regions in the Northwest Atlantic (Figure 4): the Labrador Sea, the Gulf of Maine, the Gulf Stream, the Florida Current (Gulf Stream off of the southeastern US), and the Sargasso Sea (20-35°N).

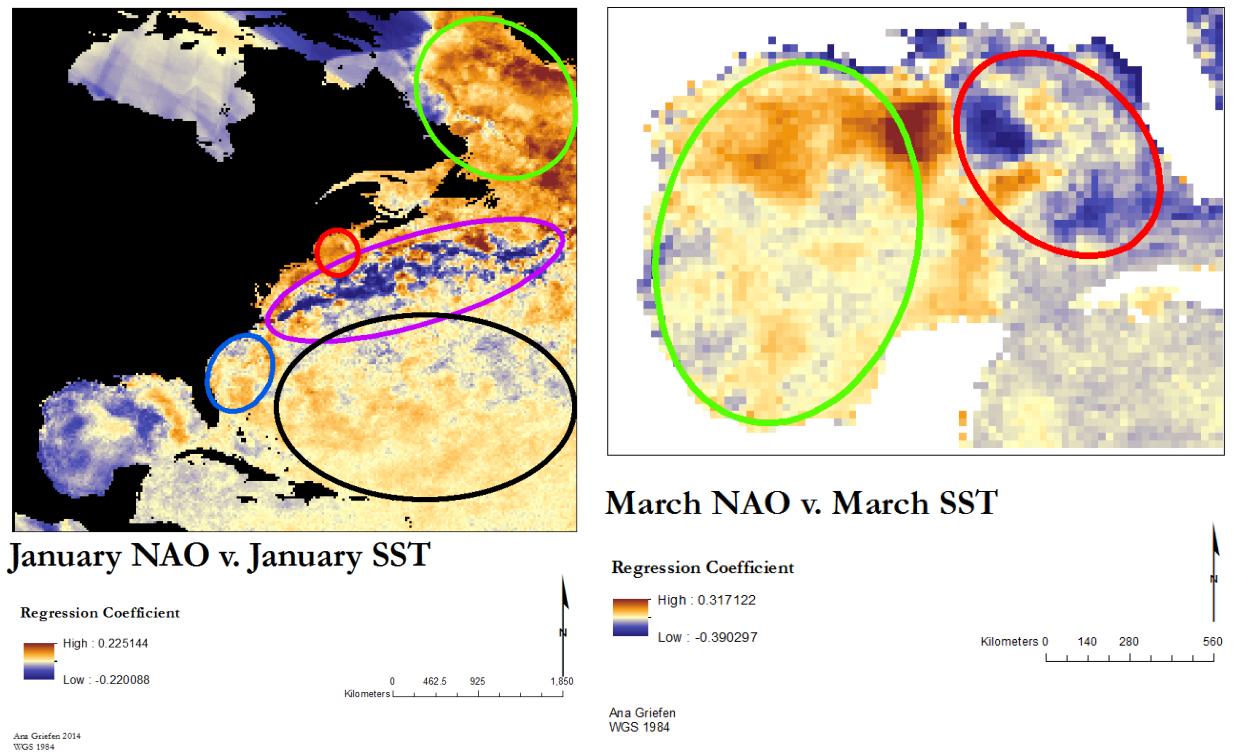


Figure 4. Correlation regions identified via visual assessments. On the left: green = Labrador Sea; red = Gulf of Maine; purple = the Gulf Stream; blue = the Florida Current; black = the Sargasso Sea. On the right: green = the western Gulf of Mexico; red = the West Florida Shelf.

We identified two correlation regions in the Gulf of Mexico (Figure 4): the West Florida Shelf, and the western Gulf. We noticed significant correlation areas along the coastline, but did not define the coastline as a region.

Curve Fit regression outputs (Figure 5) illustrated spatial patterns on scales that were relative to each individual month. Each of the identified regions was habitually delineated by groupings of similar coefficients, differentiating them from other areas, regardless of month. However, these groupings were not always significantly correlated.

$R^2$  values ranged from zero to approximately 0.5-0.6 for most months in the Northwest Atlantic. The highest  $R^2$  observed was 0.79 in the April NAO v. October SST regression. The  $R^2$  values in the Gulf of Mexico were typically lower, ranging from zero to approximately 0.3-0.4. The highest observed  $R^2$  was 0.70 during the June NAO v. June SST regression. Pixels with relatively high  $R^2$  values and low, significant p-values ( $<0.05$ ) indicated with confidence that a relatively high percentage of SST variability was correlated with the monthly NAO index. High p-values ( $>0.05$ ) indicated model uncertainty. I.e. observed  $R^2$  and coefficient values were unreliable for the assessment of the linear relationship between SST and the NAO.

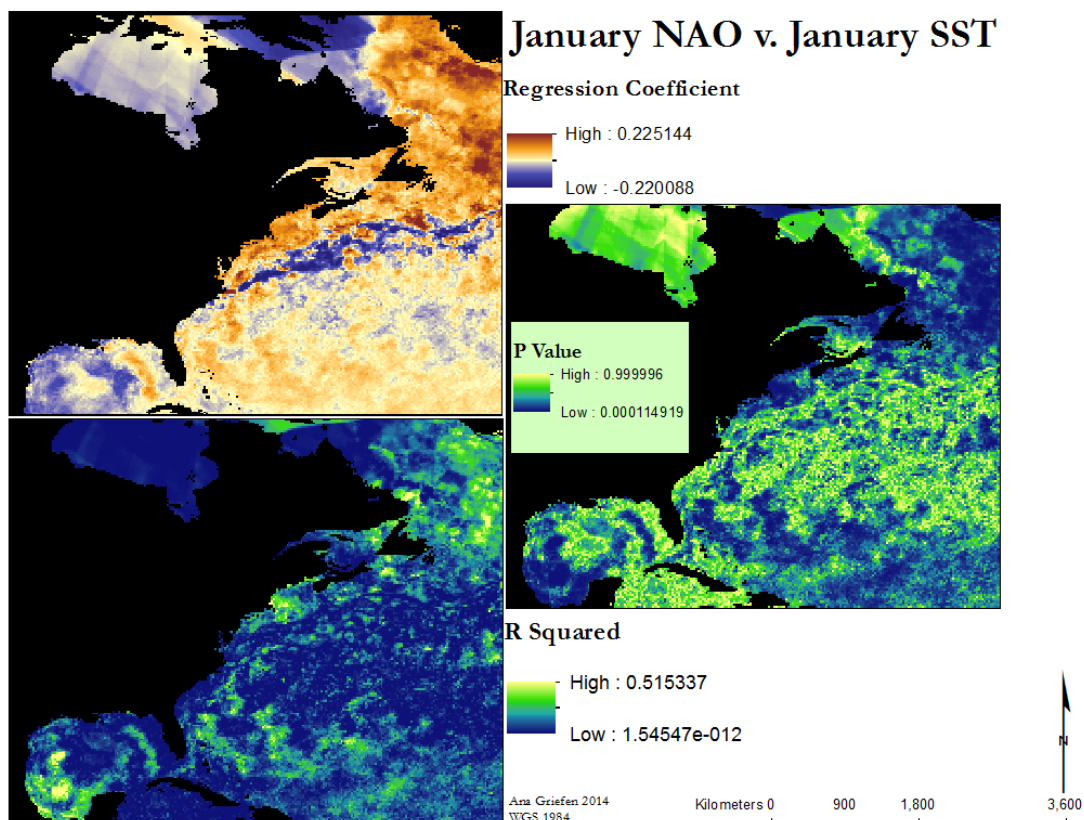


Figure 5. Typical results of Curve Fit raster analysis: (clockwise) regression coefficient, p-value, and  $R^2$  for the concurrent regression between January SST and January NAO index.

In both the NW Atlantic and the Gulf of Mexico, coefficient magnitude, direction, and correlation significance varied temporally by month. In addition, correlation significance of each region did not necessarily coincide with the significance of other regions during each month. The spatial patterns were highly variable.

We did not find convincing seasonal patterns. Winter months (December, January, February), fall months (September, October, November), spring months (March, April, May), and summer months (June, July, August) were not more related to each other than to other months. We also did not find consistent comparable or contrasting patterns between the concurrent regressions and the time-lagged regressions. In other words, neither consistently illustrated more or less distinct spatial patterns. However, the concurrent regression results seemed to be more consistent with each other month to month.

Although we found no overwhelmingly discernible differences between concurrent and time-lagged regressions month to month, both types resolved similar relative spatial patterns that resulted in the selection of our correlation regions.

#### **4.2 Spatial and temporal analysis - fisheries distribution and the NAO**

The results of our spatial pattern visual assessment were used to identify areas to analyze variability of fisheries catch and distributions with the NAO. However, not all of the identified regions were included, and one region was divided based on the fishery data points themselves. There were no longline data points in the Labrador Sea, and few in the Gulf of Maine. As a result, those regions were not included in the fisheries catch and distribution analysis. Due to observed clustering of fishery data points in the Sargasso Sea (Figure 2), the points were divided into three groups: south of 25°N, between 25-30°N, and north of 30°N.

Most of these regressions returned low  $R^2$  values with significant p-values (Table 1), indicating with confidence the inability of our simple regression models to explain variability of tuna and swordfish catch and distribution with the NAO as a single explanatory variable. I.e. the monthly NAO index by itself explains a very small percentage (represented by  $R^2$  value) of SST variability. The level of confidence of that relationship is high (represented by p-values  $<0.05$ ). However, several regressions highlighted yellow in Table 1 produced low  $R^2$  values with large ( $>0.05$ ), insignificant p-values. A couple p-values (Sargasso Sea north of  $30^{\circ}\text{N}$ , latitude: 0.724 and Gulf of Mexico West FL Shelf, tuna catch: 0.68) are high enough to suggest possible type II error. This means the model may be suggesting no relationship when there is a relationship. Examples of the resulting scatterplots are provided in Figures 6, 7, and 8, and the rest of the plots are provided in Appendix B. These plots illustrate the limitations of the NAO index as an explanatory variable. Despite varying sample sizes-the number longline data points-the dependent variables were always clumped discretely by NAO index. Further discussion of results is provided in the following section.

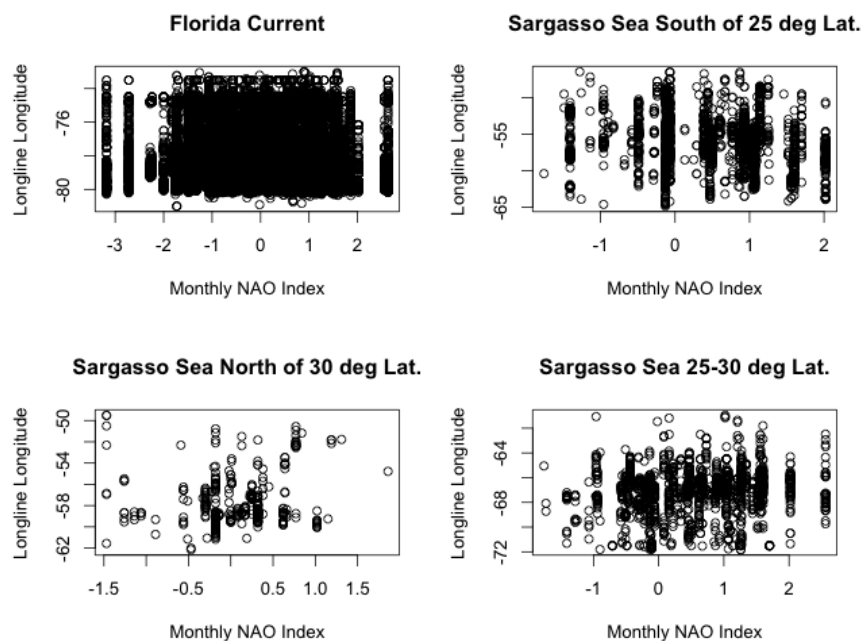


Figure 6. Monthly NAO index v. fisheries distribution by longline longitude. The regression for the Sargasso Sea north of  $30^{\circ}\text{N}$  had the lowest number of data points (observations), a low  $R^2$ , and a large ( $>0.05$ ), insignificant p-value.

Table 1. Fishery catch (tuna and swordfish) and distribution (latitude and longitude) regression analysis results. Highlighted p-values are greater than the 0.05 significance level.

<b>NAO v. Latitude</b>			
Correlation Region	R <sup>2</sup>	p-value	# observations
FL Current	0.006427	<2.2e-16	47346
Gulf Stream	0.007159	< 2.2e-16	50316
Sargasso Sea (south of 25°N)	0.02085	3.17E-14	2737
Sargasso Sea (north of 30°N)	0.0003467	0.724	362
Sargasso Sea (between 25-30°N)	0.03214	3.17E-13	1631
Gulf of Mexico (West FL Shelf)	0.001206	0.004154	6812
Gulf of Mexico (Western Region)	0.0002414	0.0001136	61699
<b>NAO v. Longitude</b>			
Correlation Region	R <sup>2</sup>	p-value	# observations
FL Current	0.001809	<2.2e-16	47346
Gulf Stream	0.003048	< 2.2e-16	50316
Sargasso Sea (south of 25°N)	0.01328	1.48E-09	2737
Sargasso Sea (north of 30°N)	0.009697	0.06125	362
Sargasso Sea (between 25-30°N)	0.01668	1.71E-07	1631
Gulf of Mexico (West FL Shelf)	0.002513	3.48E-05	6812
Gulf of Mexico (Western Region)	0.0005434	7.00E-09	61699
<b>NAO v. Tuna catch</b>			
Correlation Region	R <sup>2</sup>	p-value	# observations
FL Current	0.0002272	0.00104	47346
Gulf Stream	0.000486	1.29E-05	39136
Sargasso Sea (south of 25°N)	0.00084	0.1295	2737
Sargasso Sea (north of 30°N)	0.008174	0.08584	362
Sargasso Sea (between 25-30°N)	0.0003729	0.4362	1628
Gulf of Mexico (West FL Shelf)	2.44E-05	0.6837	6812
Gulf of Mexico (Western Region)	1.60E-05	0.3211	61699
<b>NAO v. Swordfish catch</b>			
Correlation Region	R <sup>2</sup>	p-value	# observations
FL Current	0.0003607	3.58E-05	47346
Gulf Stream	8.72E-05	0.03617	50316
Sargasso Sea (south of 25°N)	0.002935	0.004581	2737
Sargasso Sea (north of 30°N)	0.07345	1.63E-07	362
Sargasso Sea (between 25-30°N)	0.0101	4.85E-05	1628
Gulf of Mexico (West FL Shelf)	0.0001179	0.3703	6812
Gulf of Mexico (Western Region)	0.008023	< 2.2e-16	61699

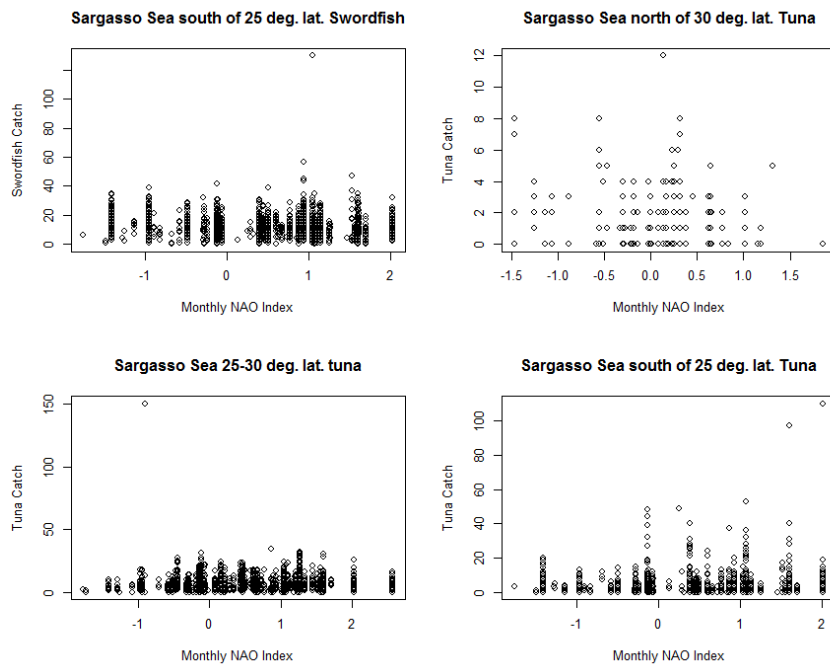


Figure 7 Monthly NAO index v. tuna fishery catch and swordfish catch in the Sargasso Sea regions. Each tuna regression returned insignificant p-values. The swordfish regression, which had a significant p-value, is provided for comparison.

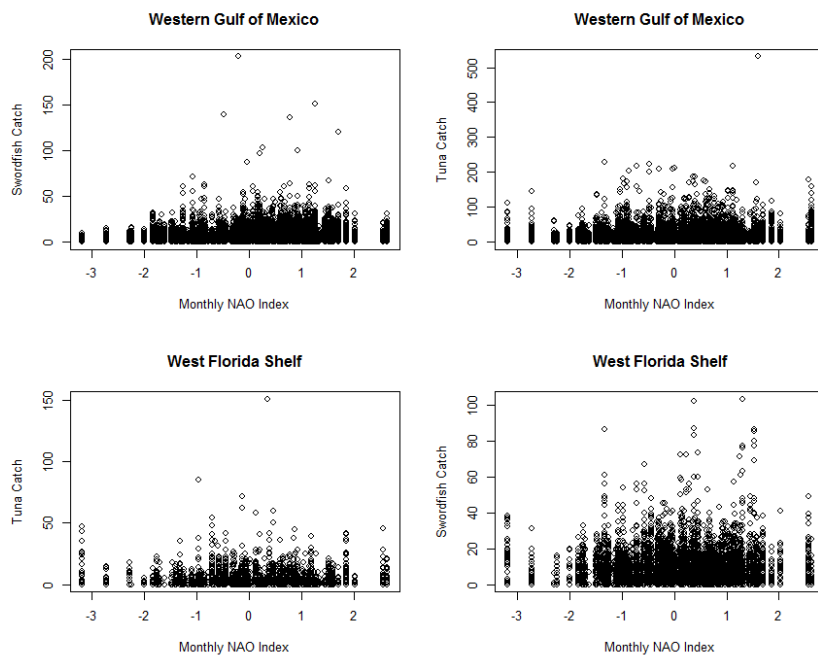


Figure 8. Tuna and swordfish catch by region in the Gulf of Mexico. The regression for Swordfish in the Western Gulf had a significant p-value, the others had insignificant p-values.



## 5. Discussion

The relationship between the NAO and SST is complex and correlation does not imply causation. Studies suggest ocean forcing via SST anomalies is more significant than atmospheric forcing via the NAO, particularly in the Gulf Stream (Wang et al., 2004; Hurrell et al., 2003). Complexity and ocean forcing via SST may explain why we did not find substantial seasonal patterns with either the concurrent or time-lagged regressions. We used the NAO as the explanatory variable (atmospheric forcing) because Curve Fit only allows raster datasets (our SST rasters) as the dependent variable. Regressions with SST as the explanatory variable incorporating a variety of time lags might produce more insightful results.

Additionally, the monthly index values of the NAO are singular values describing the phase of the North Atlantic Oscillation for the entire Atlantic Ocean (Stenseth et al., 2003), which may obscure regional variation. Further analysis utilizing the pressure height anomalies which are used to calculate the NAO index at a given time might provide greater acuity.

Although linear regressions are simple models, which cannot fully account for the complexity of the system between the atmosphere and the ocean, Curve Fit analysis facilitated the characterization of continuous spatial and temporal change by month across our study regions, which allowed us to identify smaller regions of relatively high explained variance (De Jager and Fox, 2013). The raster classification scales were relative to the individual month, and not the entire data set, which may have obscured seasonal temporal patterns. Each scale had to be considered in the context of that individual month. For example, the Gulf of Mexico regressions between November NAO v. November SST and May NAO v. November SST (Appendix A.2) displayed raster coefficients which are all positive with relatively insignificant correlations. This insignificance would have been overlooked if the classification scales were not considered.

Furthermore, our visual assessments of the output raster surfaces were somewhat subjective and others might interpret them differently. However, we specifically identified regions that expressed relatively high  $R^2$  values (correlation) and low p-values (significance), and we are confident in our interpretation of spatial patterns because the identified regions in the NW Atlantic and in the Gulf of Mexico are consistent with the dominant circulation patterns of the ocean.

In the NW Atlantic, the Florida Current is the initial segment of the Gulf Stream, and together they provide the western, warm water border of the Sargasso Sea. The Greenland and Labrador Currents influence the Labrador Sea, and bring cold water down to the Gulf of Maine. Although we identified these regions based on recurring spatial patterns, they were not necessarily homogenous. Fronts and eddies produced variability within the Gulf Stream and the Labrador Sea, and areas we considered to be in the Sargasso Sea varied by proximity to boundary currents, such as the Antilles Current, the Florida Current, and the Gulf Stream.

In the Gulf of Mexico, the identified regions appeared to be associated with the highly variable Loop Current and subsequent eddies. As a result, these regions were harder to define than in the NW Atlantic, and we conservatively identified two regions. The Gulf of Mexico bathymetry likely contributed to variability, particularly in differentiating the West Florida Shelf, which is a large shallow area. We expected analysis at a smaller scale to refine results relative to analysis at a larger scale, such as the Northwest Atlantic region. The results suggest that greater variability of spatial patterns was detected; maximum  $R^2$  were consistently lower throughout the Gulf of Mexico than maximum  $R^2$  values in the NW Atlantic. Consequently, defining regions in the Gulf of Mexico was more difficult.

In addition, consistency with dominant ocean circulation patterns reinforces the dynamic relationship between atmospheric climate variability, the NAO, and the ocean. Physical parameters are constantly influencing other parameters and single variable models do not account for multiple

influences. This is reflected by the areas without significant correlation, as well as the results from regressions with fisheries catch and distribution.

Again, calculating regressions between SST and the NAO on a monthly basis allowed us to identify different spatial patterns of relative correlation by month. If we had not separated regressions by month, contrasting relationships may have confounded our results. I.e. if the correlation between SST and the NAO was positive for one month, and negative for another, there may have been no significant correlation overall. Separating regressions by month prevented expression of this potential confounding effect.

Unfortunately, we did not separate regressions between fisheries catch and effort and the NAO by month. This is the predominant issue with our analysis. The regressions between fisheries catch and effort with the NAO included fishery data from all months, indexed with the monthly NAO, across all years. This prevented us from identifying potential correlations by individual month, and introduced more variation than the explanatory variable, the NAO, was able to explain.

As a result, the significance and lack of correlation in our fisheries models does not conclude that the North Atlantic Oscillation has no effect on fisheries catch or distribution. Rather, the low  $R^2$  and significant p-values suggest that simple linear models with the NAO as the explanatory variable did not explain variance of fisheries catch and distribution in the context of our study. Conversely, high p-values suggest possible type II error, indicating an underestimation of the relationship between SST and the NAO. Interestingly, the regression model for NAO v. longitude in the Sargasso Sea north of  $30^{\circ}\text{N}$  (Figure 6) with insignificant p-value produced a scatterplot with the most distinguishable trend. This slight trend is unreliable due to the insignificant p-value although the p-value 0.06125 is not much greater than the 0.05 significance level. The inability of our models to explain variance could be the misapplication of a linear relationship, i.e. the relationship between the variables is not linear (Stenseth et al., 2003). Assumption of a linear relationship could also be an

explanation for the potential type II error, which suggests no relationship when there may be a relationship in the opposite direction.

Additionally, the input variables themselves may be limiting factors. Again, the characterization of the NAO as a single variable for the entire region may reduce the ability to detect clear relationships. Theoretically, however, low variability of the explanatory variable could actually be increasing the correlation between the explanatory and dependent variables, and higher variability of the explanatory variable could further reduce the correlation we observed. Potential errors in the calculation of SST anomalies could have also affected our results.

Most likely, models that incorporate other environmental variables, such as sea surface height, distance to fronts, currents, or bathymetry, as well as changes in fisher behavior, will be better at explaining fisheries catch and distribution changes with a changing climate (Jorgensen et al., 2012; Cheung et al., 2011). Fisheries dynamics are also highly dependent on biological interactions, which our study did not consider (Lehodey et al., 2006). Our models and visual assessment were overly simplistic and more analysis is necessary to provide insight into relationships between fisheries distribution and the NAO. Fisheries analysis should also be recalculated by individual month.

## **6. Conclusion and policy solutions**

By assessing the magnitude, direction, and significance of regression coefficients by raster cell throughout our study regions, we identified regions of relatively high correlation between sea surface temperature and the North Atlantic Oscillation, which are consistent with the dominant ocean circulation patterns in those areas. Despite our overly simplistic exploratory analysis, pixel-level regressions with the relatively new USGS Curve Fit tool provided for characterization of spatial and temporal patterns. Our inconclusive results on the relationship between fisheries catch and

distribution with the NAO are likely indicative of ineffective model design, and not necessarily an insignificant relationship and the tools we used should not be discounted.

Considering the uncertainty of scientific models and relationships between fisheries distributions and climate variability, precautionary and adaptable management schemes should be utilized to cope with potential climate change effects on economic and political stability. Climate induced population shifts threaten international security (Pinsky et al., 2013; Cheung et al., 2010), and a variety of stakeholders with diverse values are dependent on the effective management of fisheries. The commercial and cultural value of fisheries warrants studies on climate variability and fisheries distribution. Greater insight into the relationship between climate and fisheries can refine model predictions, which managers can utilize to preempt conflicts or implement adaptable management policies (Salinger, 2013; Lehodey et al, 2006).

By examining past climate fluctuations with catch distribution over the same period, one may be able to predict where future catch distributions are likely. The NAO may be particularly insightful because the pressure indices exist as averages on a variety of scales (days, months, years), which may be useful in detecting anomalies. Similar studies have been conducted in the Pacific Ocean with ENSO events, but less has been studied with the NAO. Significant correlation of catch distribution shifts with NAO fluctuations may indicate what might happen in local regions.

Although limited in predictive capabilities, climate models can help policy managers prioritize efforts. If policy makers have a general idea of which fisheries are likely to shift, they can attempt to create policies for those fisheries that work for the present, but are flexible enough to change in the future. Without research on fishery distribution, catch distribution, climate change, and current policy regimes, governments will be ill prepared to confront new disputes. Institutions must be readily adaptable and flexible enough to cope with differences in biophysical aspects induced by climate change, as well as changes in fisher behavior.

Rigid management is not beneficial long-term, particularly if populations shift north or south with climate change. International and regional institutions and treaties that manage HMS must foster constant, open communication between signatory nations. To facilitate negotiation, countries must prioritize their stakeholder interests and clearly state objectives. Maintaining a clear understanding of priorities and areas for potential compromise will promote mutually beneficial solutions for all parties. Signatory nations should utilize international interest groups and non-governmental organizations in collaboration with their own governmental resources to assess the values of their stakeholders.

The security of HMS fisheries in the future depends on the resources invested in institutions that manage and study them today. Unfortunately, although fisheries are a huge resource in national economies, necessary funding competes with other political action agendas, such as defense. The investment of resources into scientific studies, management programs, and distributing that information is crucial to ensure economic and political stability.

Over harvesting, bycatch, subsidies, and shortsighted mismanagement of fisheries weaken the ability of fisheries to cope with change. Climate change may be an impetus for implementation of long-term sustainable practices. As for solutions, highly migratory species may always be problematic. Ultimately, the management of fisheries is actually the management of human stakeholders that utilize the resource. Thus, the fate of HMS fisheries, including tuna and swordfish, depends on human values.

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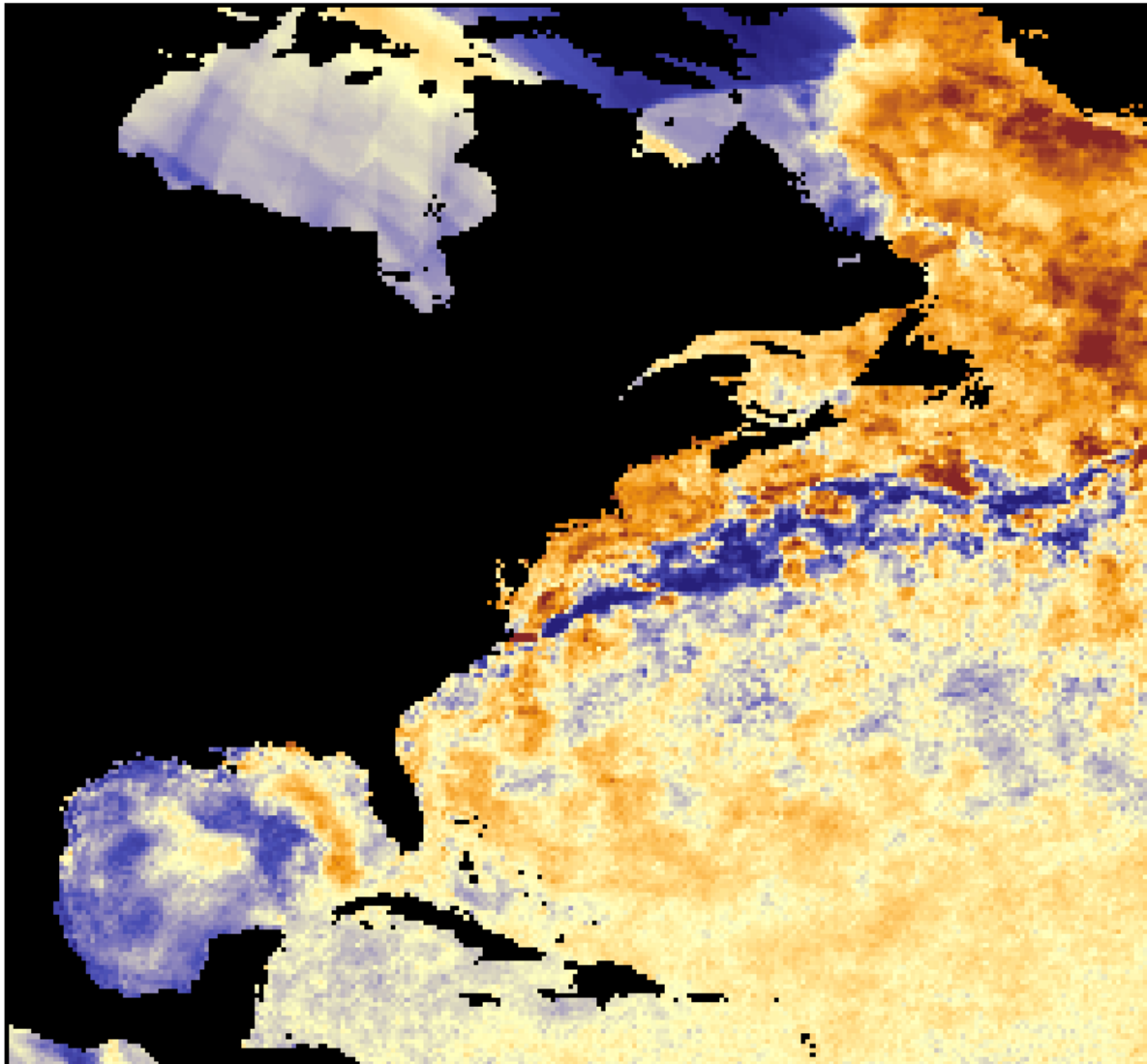


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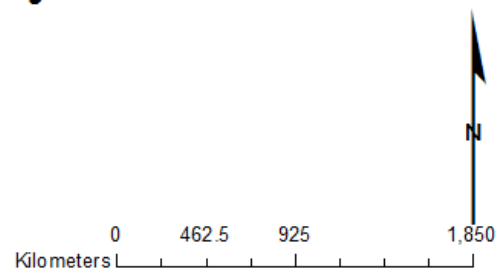
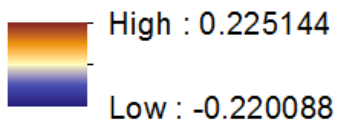
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## Appendix A.1 – Output raster surfaces

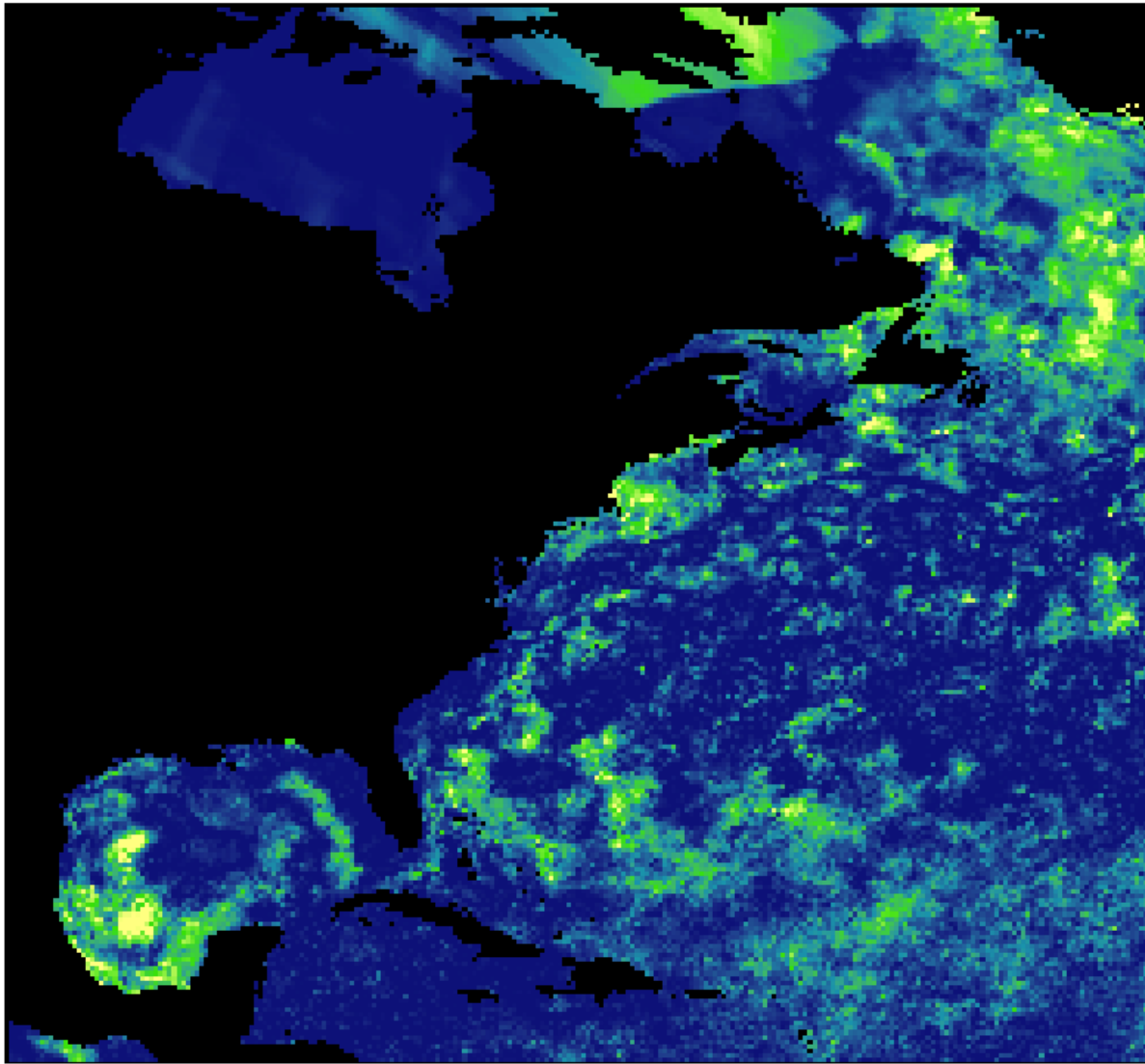


### January NAO v. January SST

Regression Coefficient

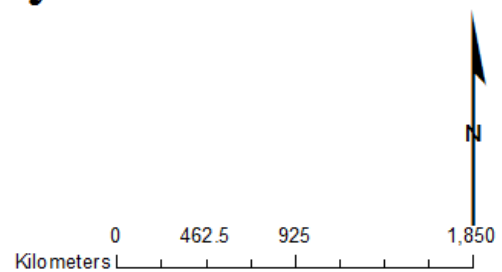
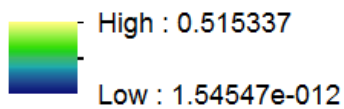


Ara Griefen 2014  
WGS 1984

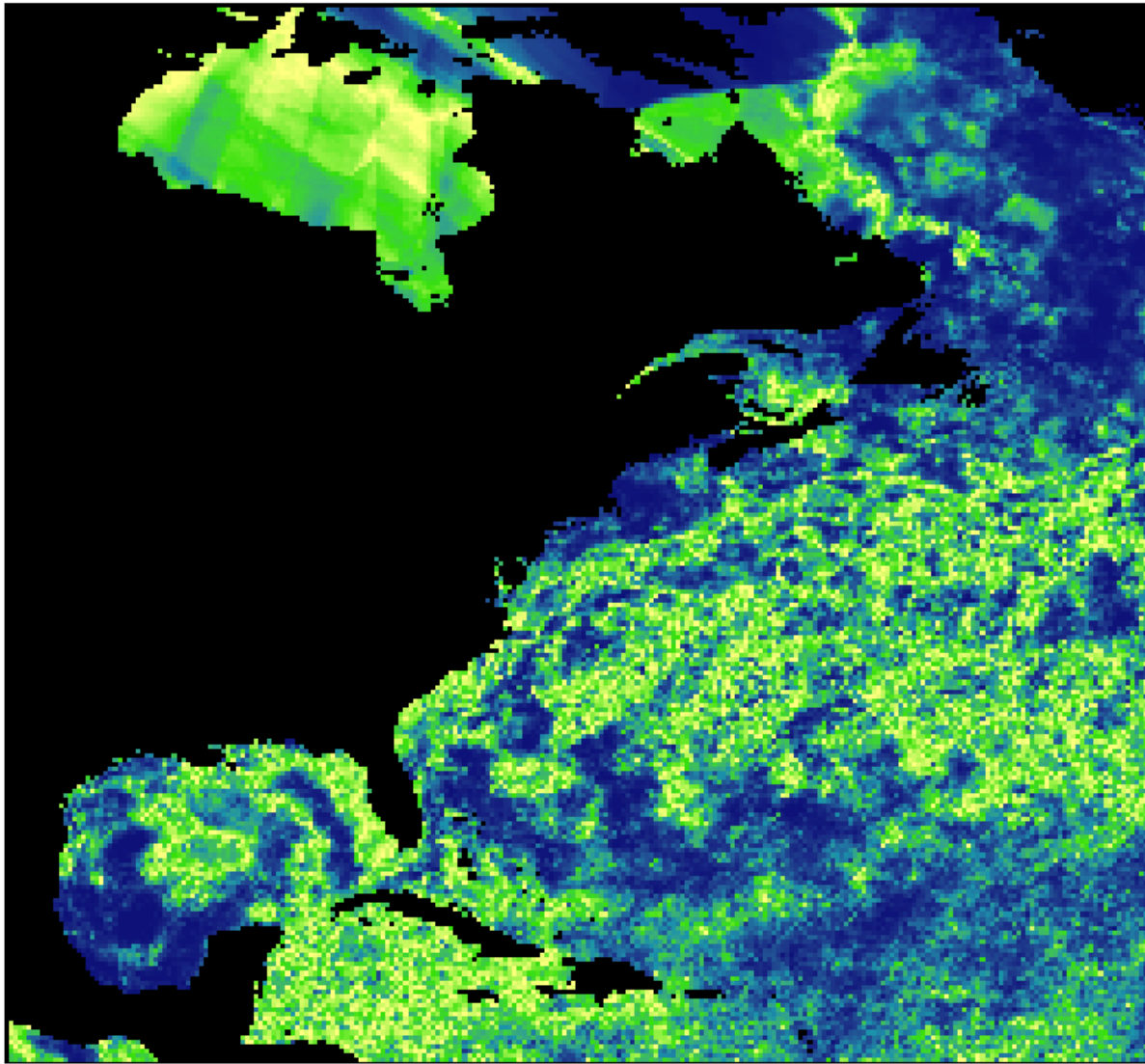


## January NAO v. January SST

R Squared

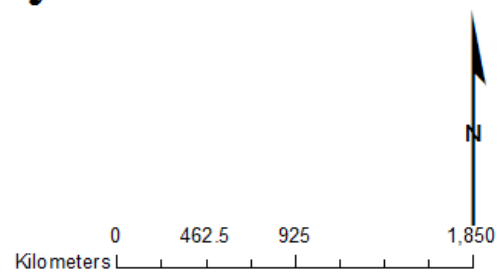
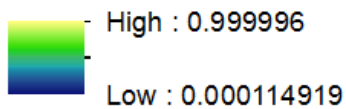


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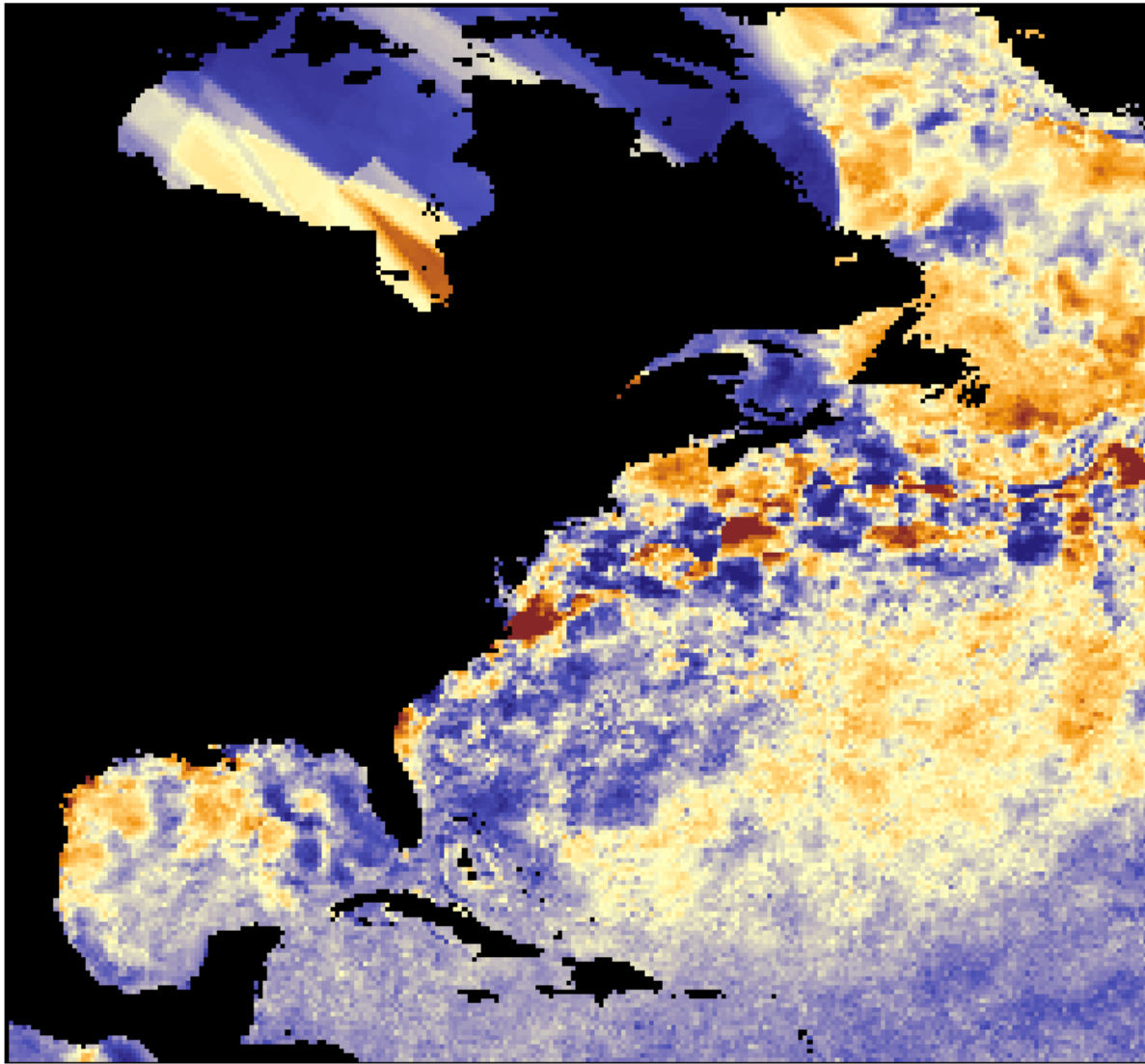


## January NAO v. January SST

P Value

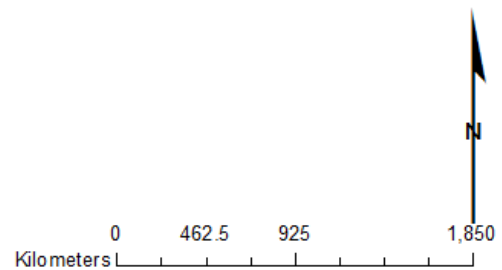
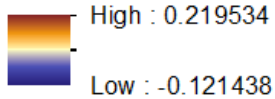


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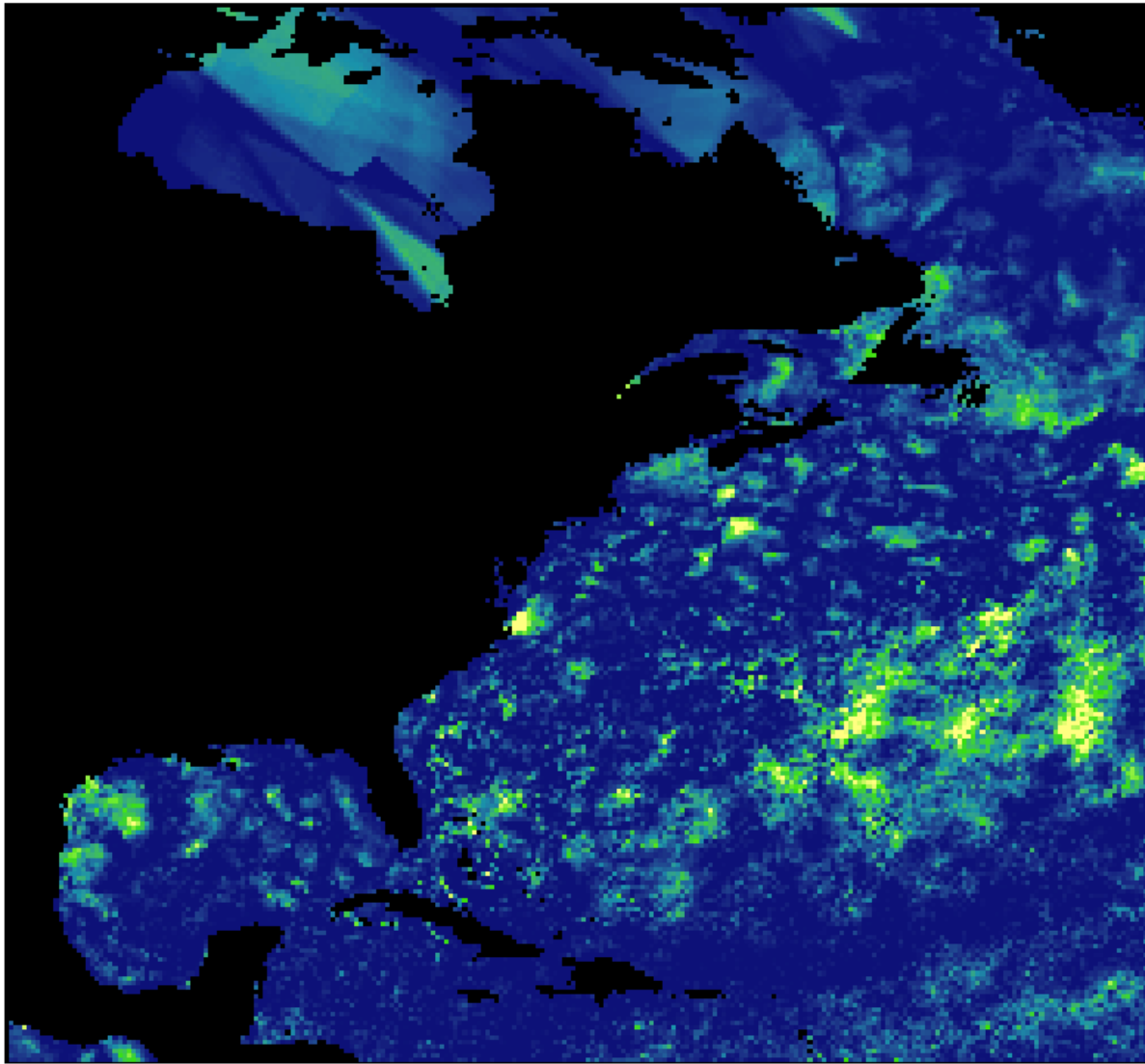


## July NAO v. January SST

Regression Coefficient

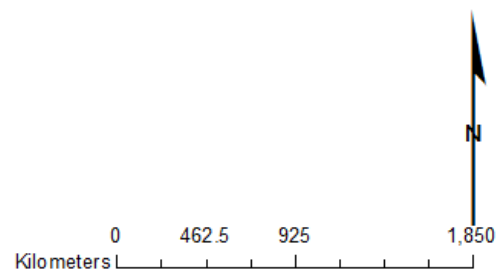
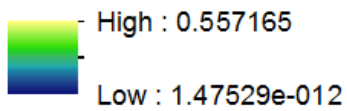


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WGS 1984



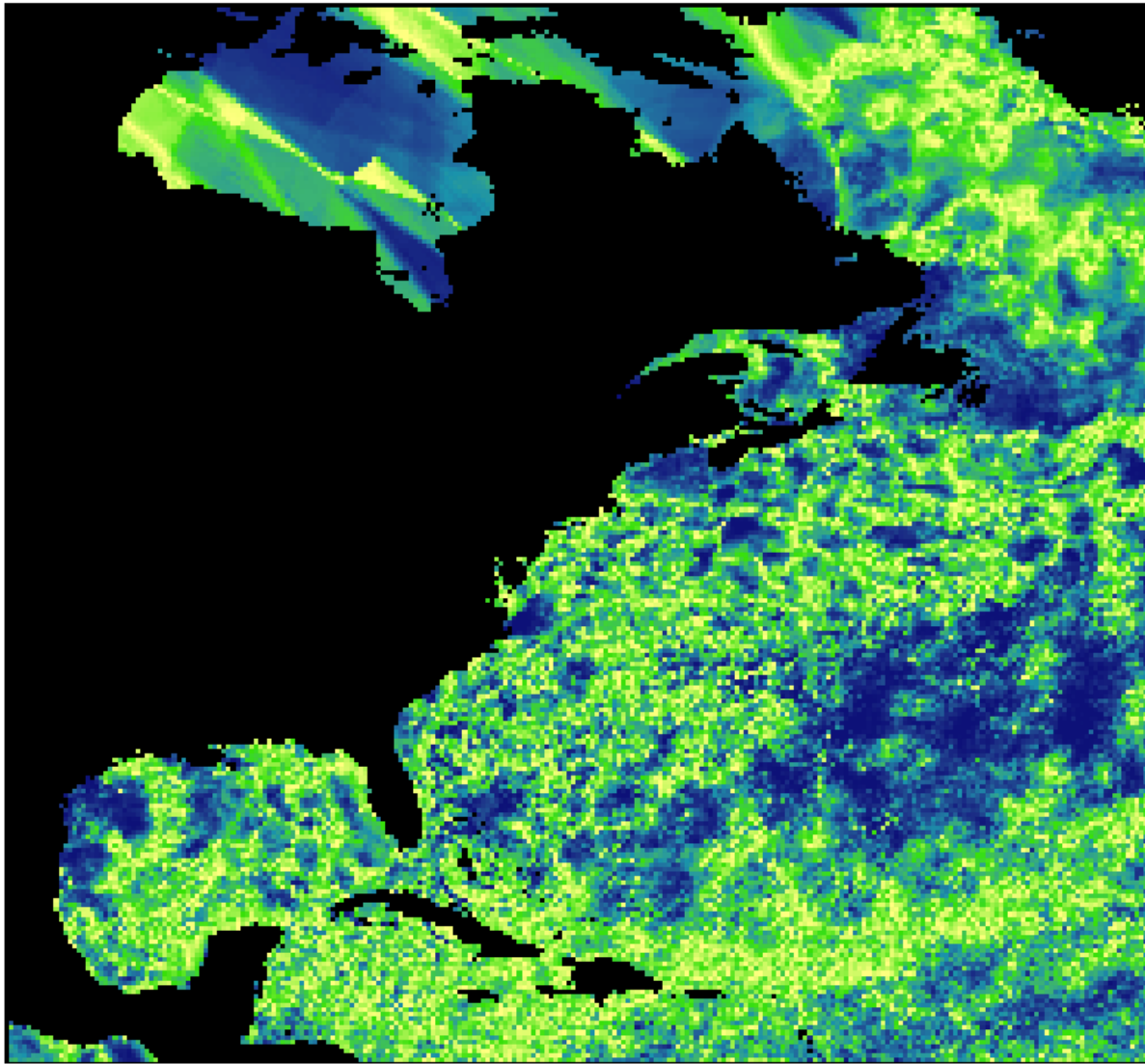
## July NAO v. January SST

R Squared



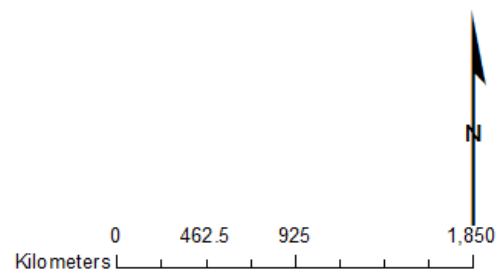
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WGS 1984



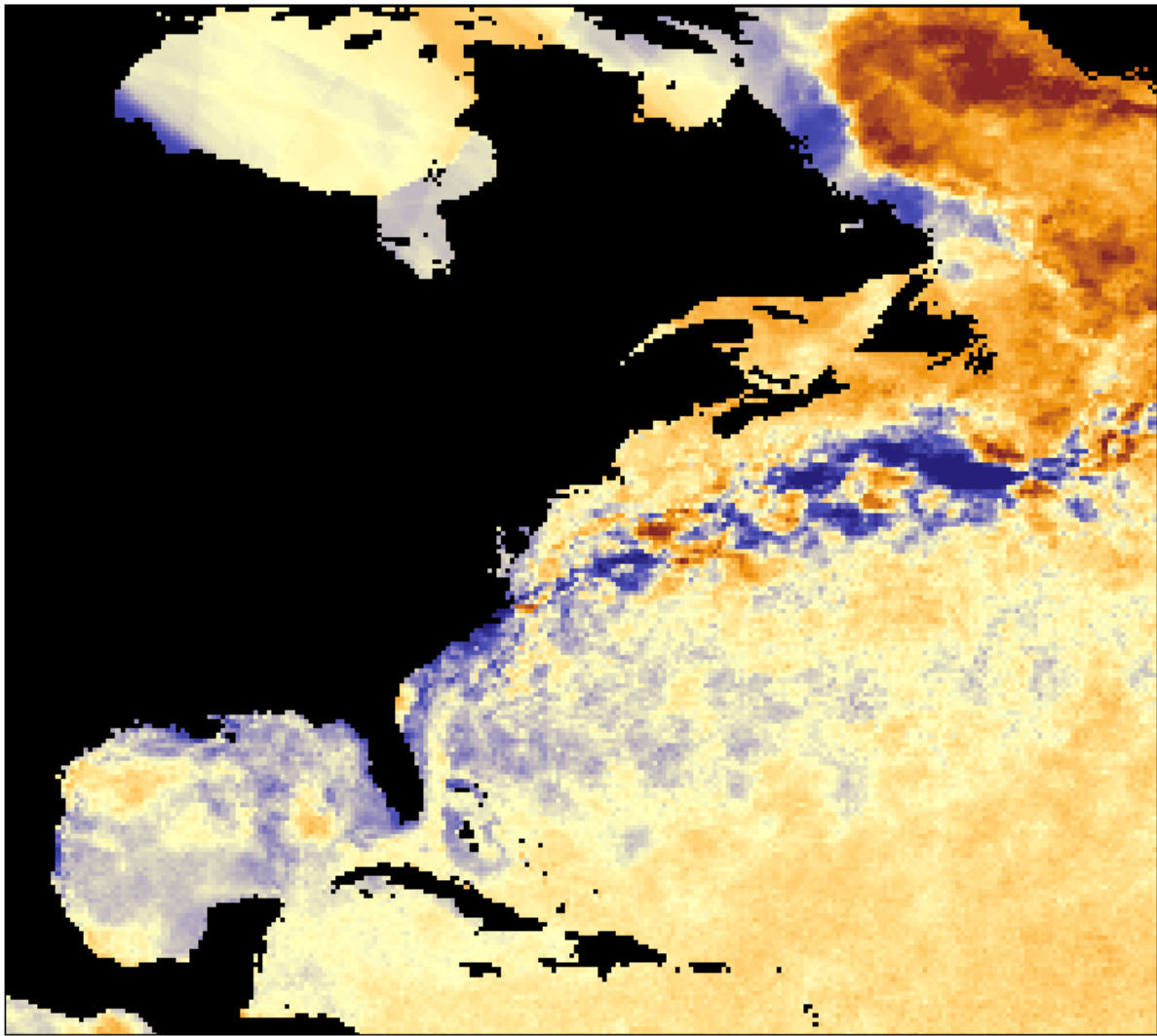


## July NAO v. January SST

P Value

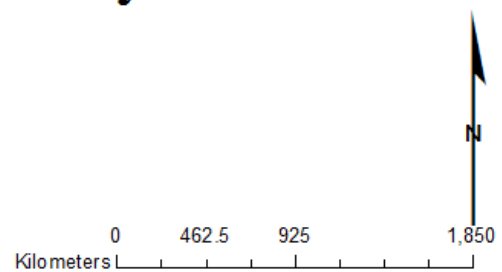
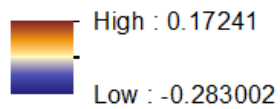


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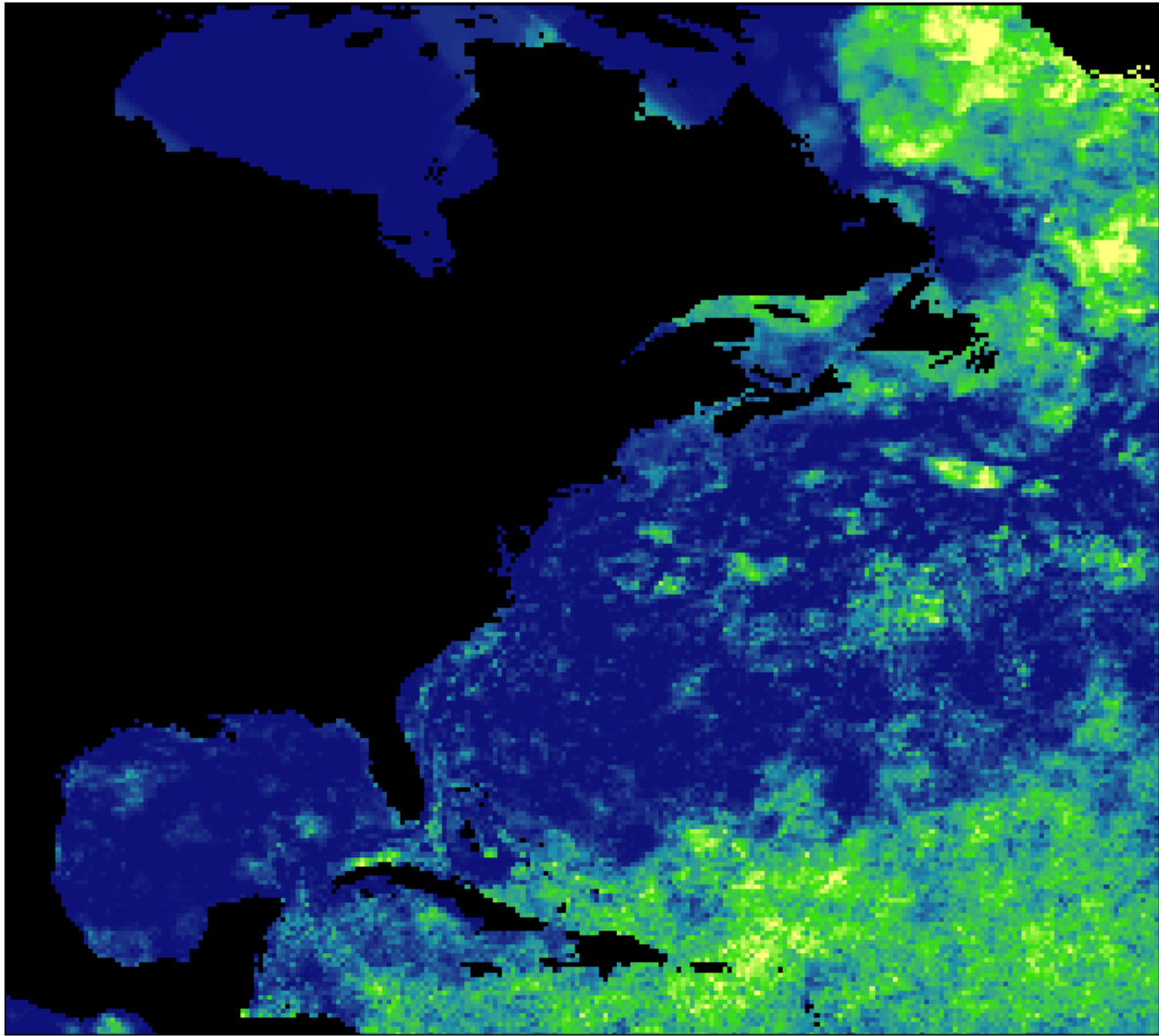


## February NAO v. February SST

Regression Coefficient

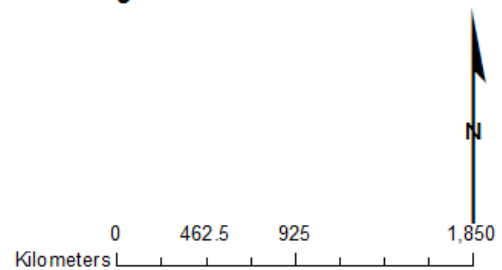
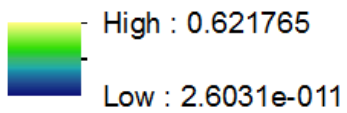


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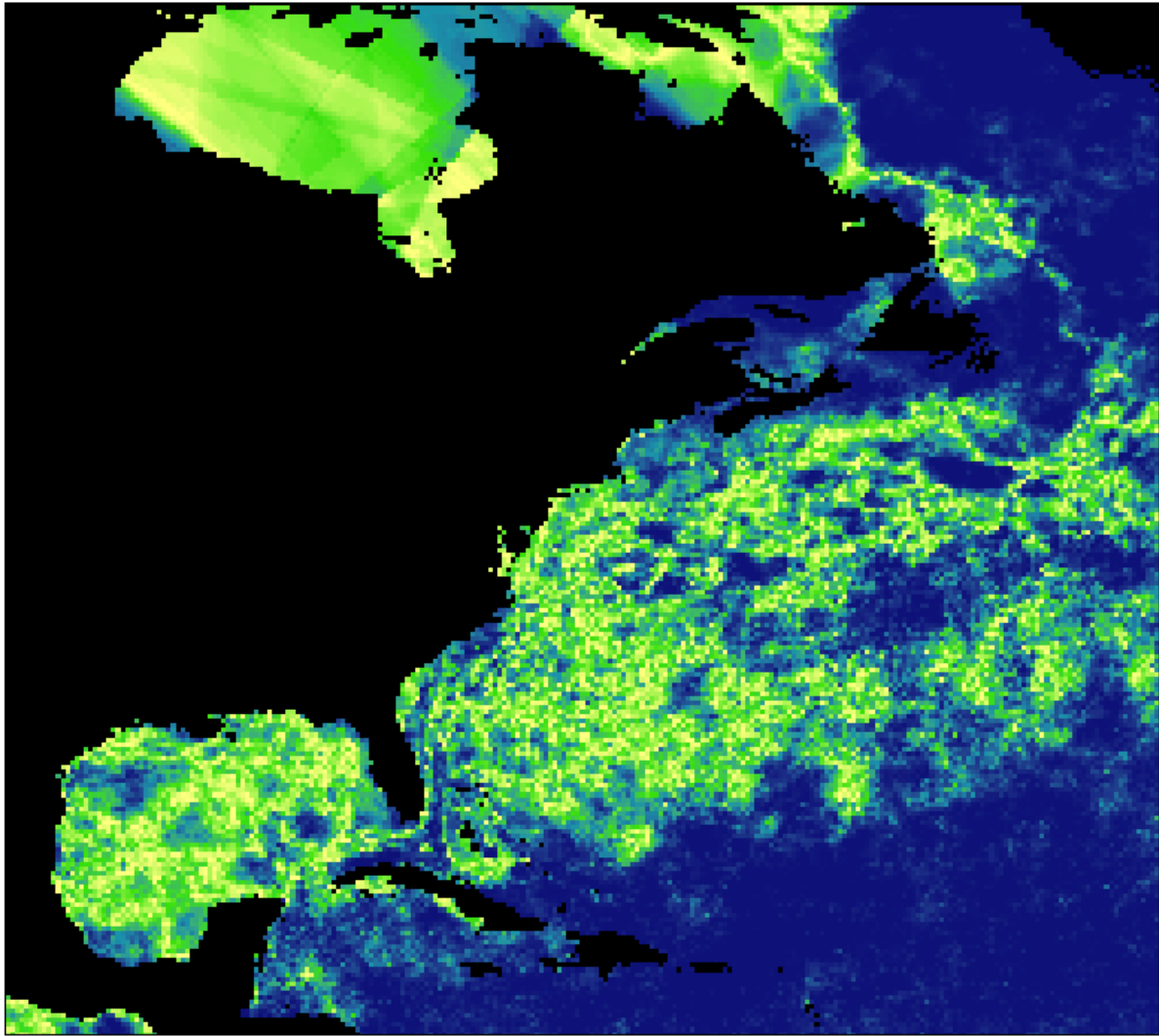


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R Squared

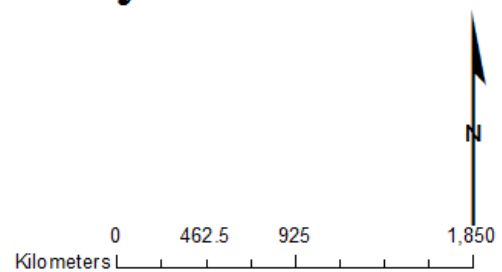
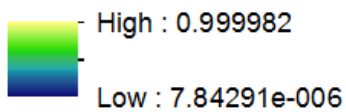


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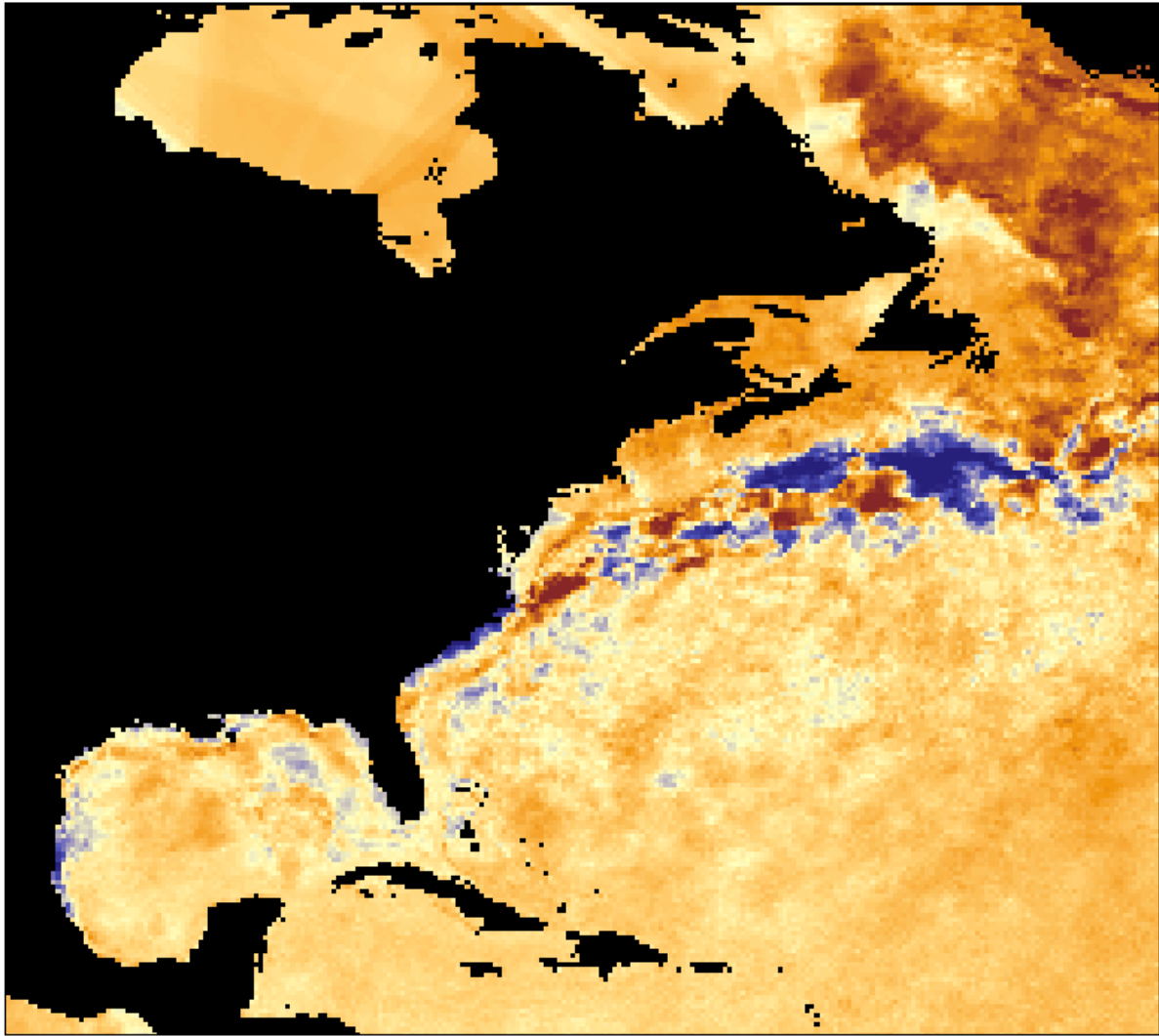


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P Value

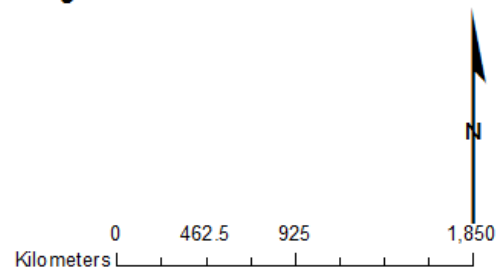
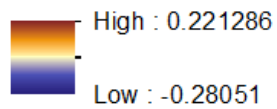


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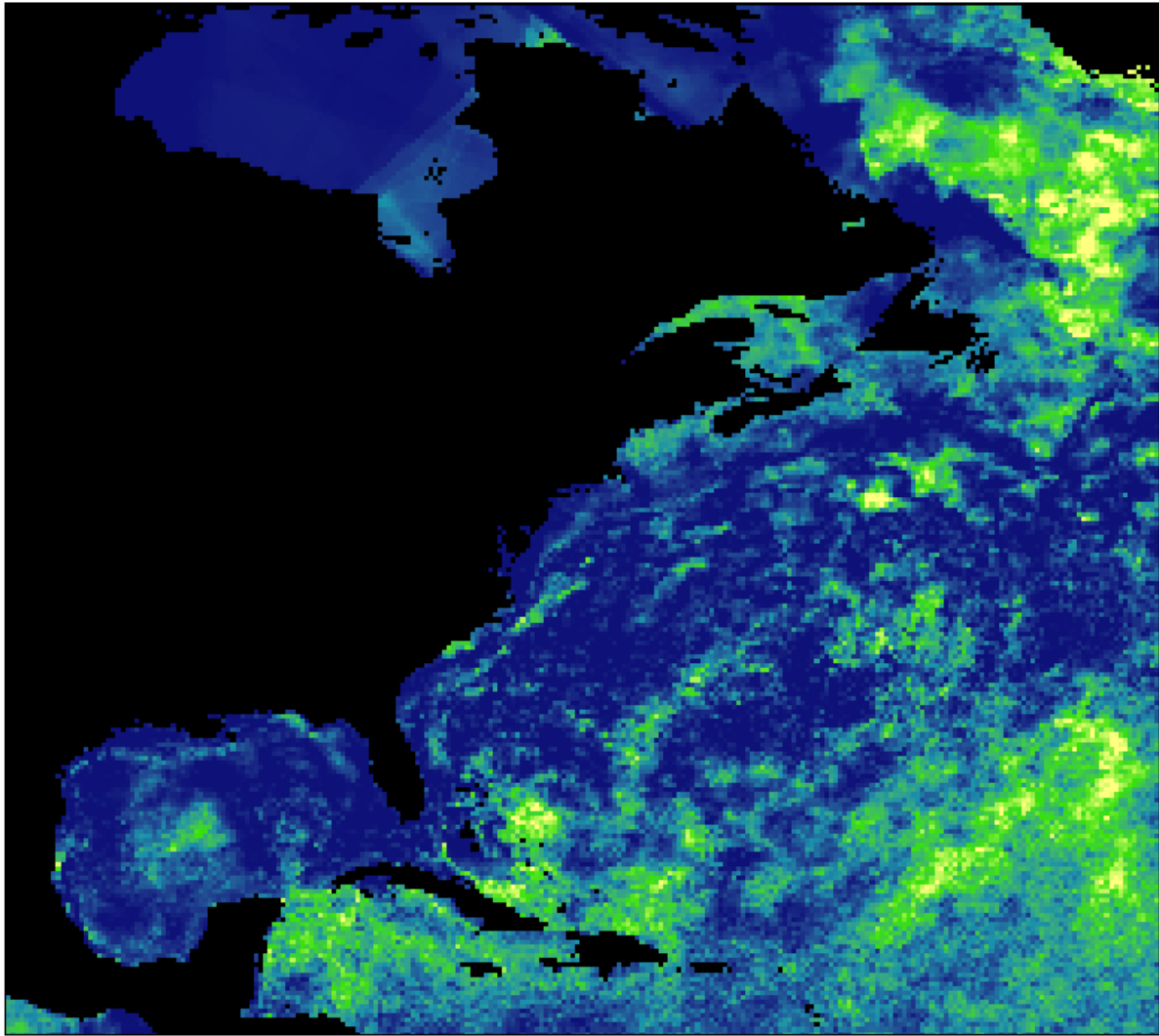


## August NAO v. February SST

Regression Coefficient

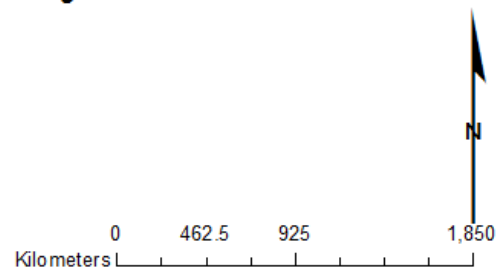
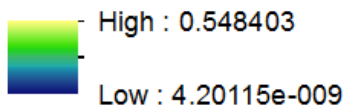


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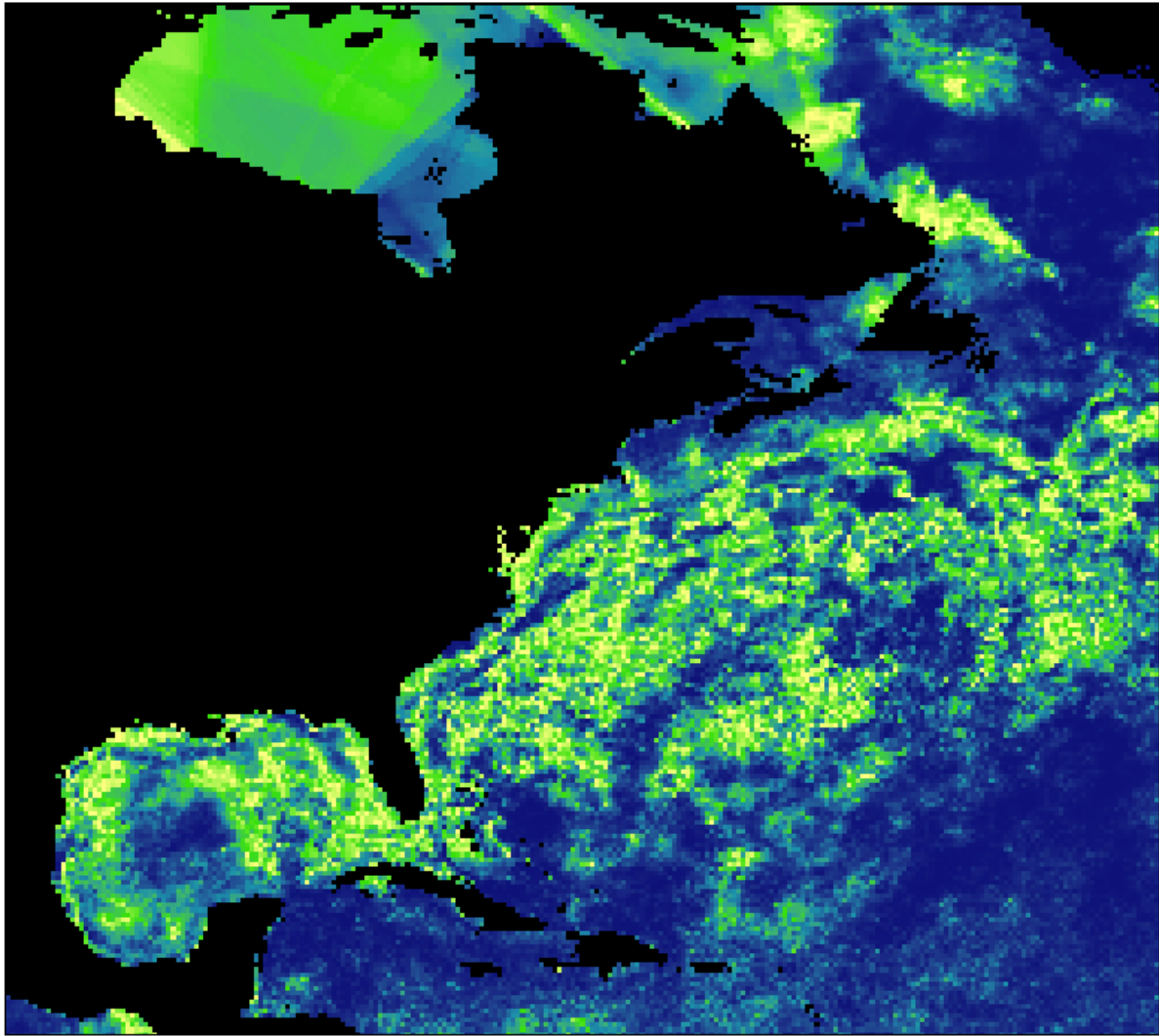


## August NAO v. February SST

R Squared

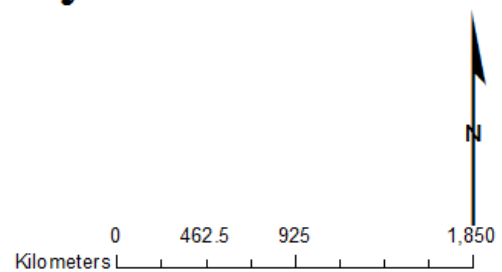
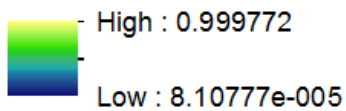


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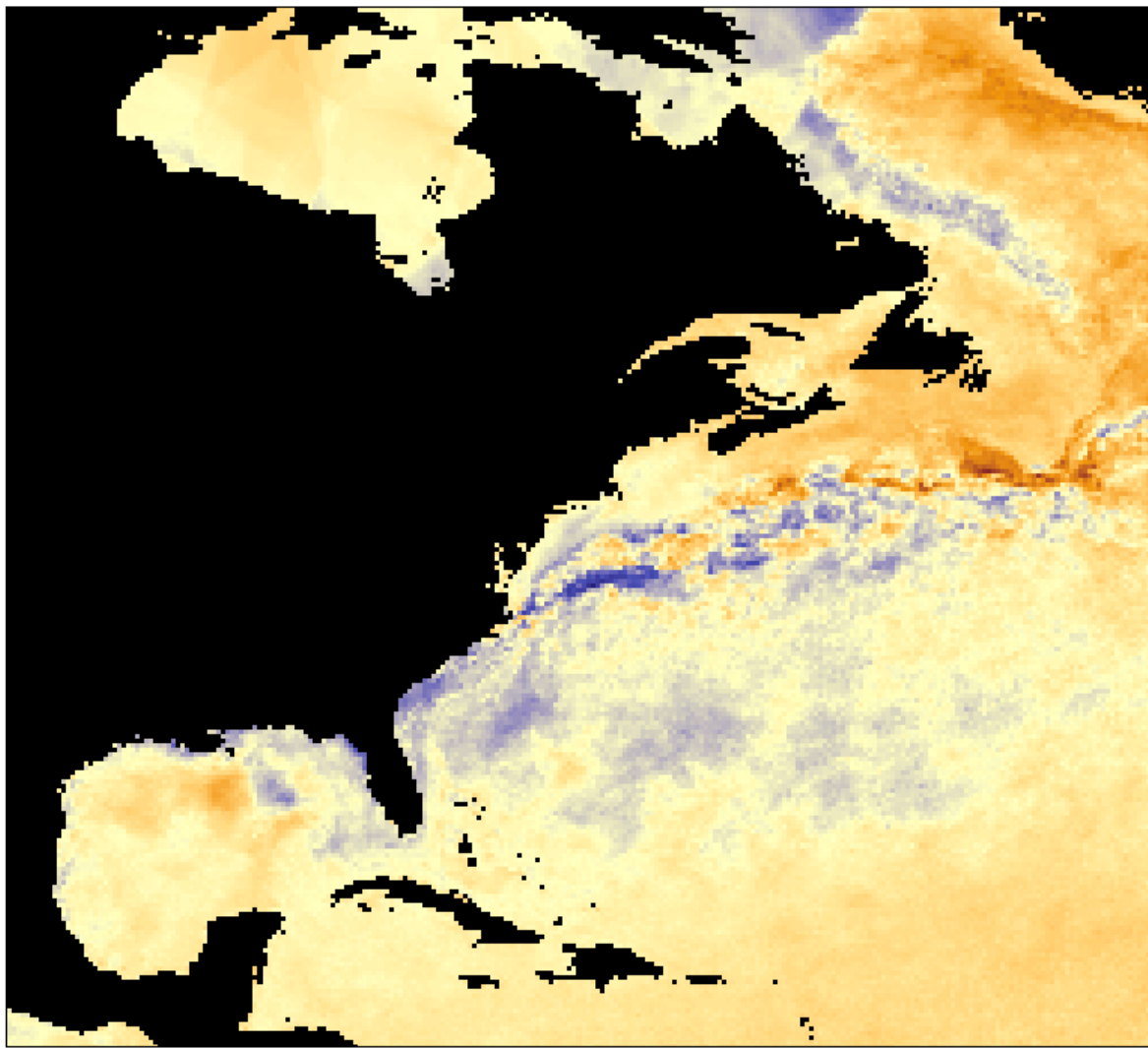
## August NAO v. February SST

P Value



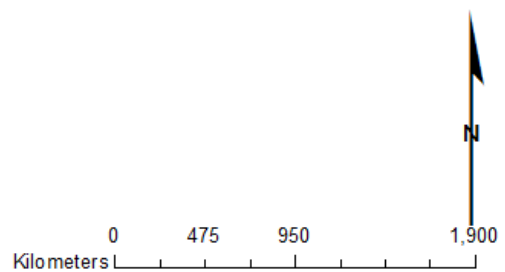
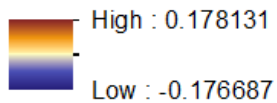
Ana Griefen 2014  
WGS 1984





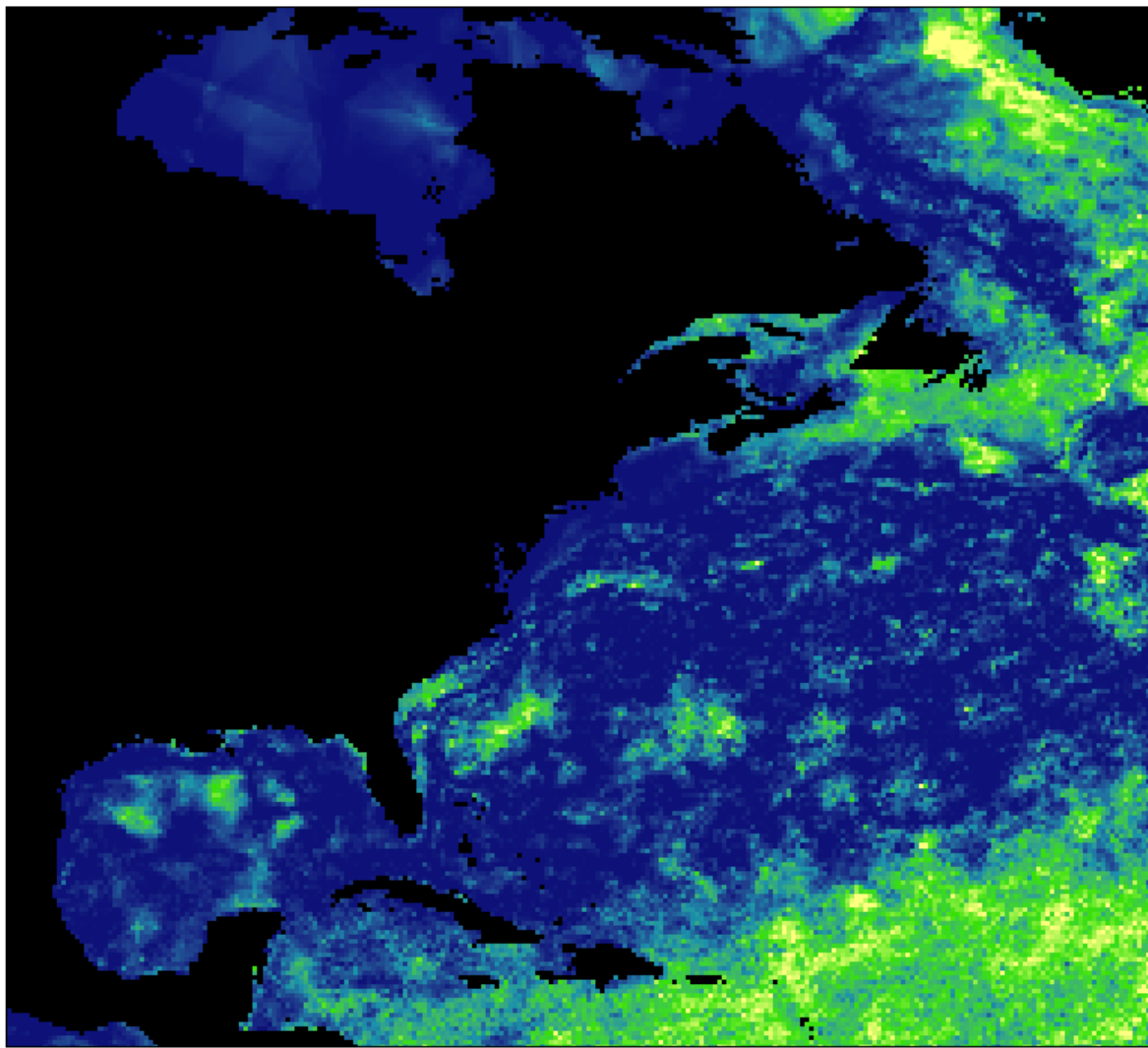
## March NAO v. March SST

Regression Coefficient



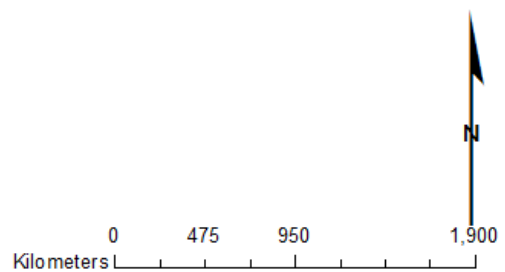
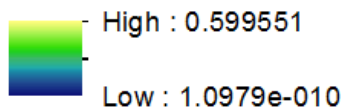
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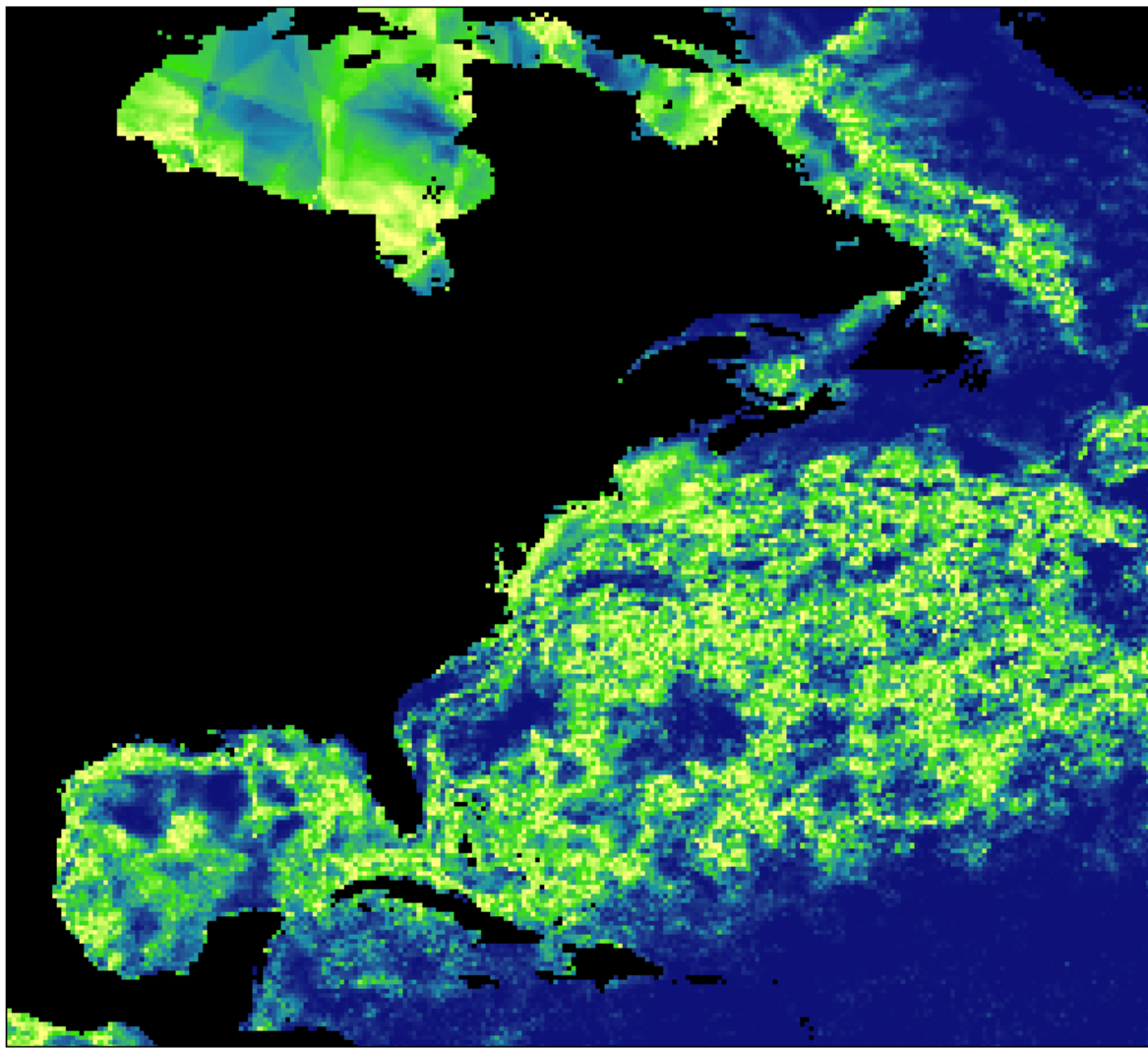


## March NAO v. March SST

R Squared

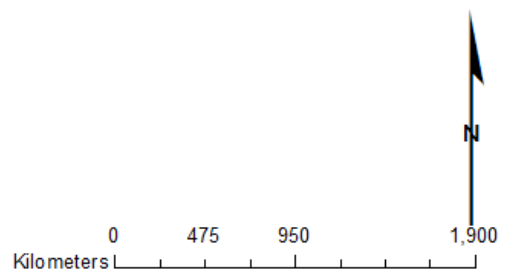
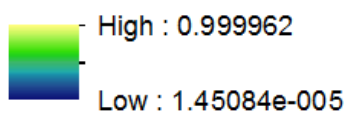


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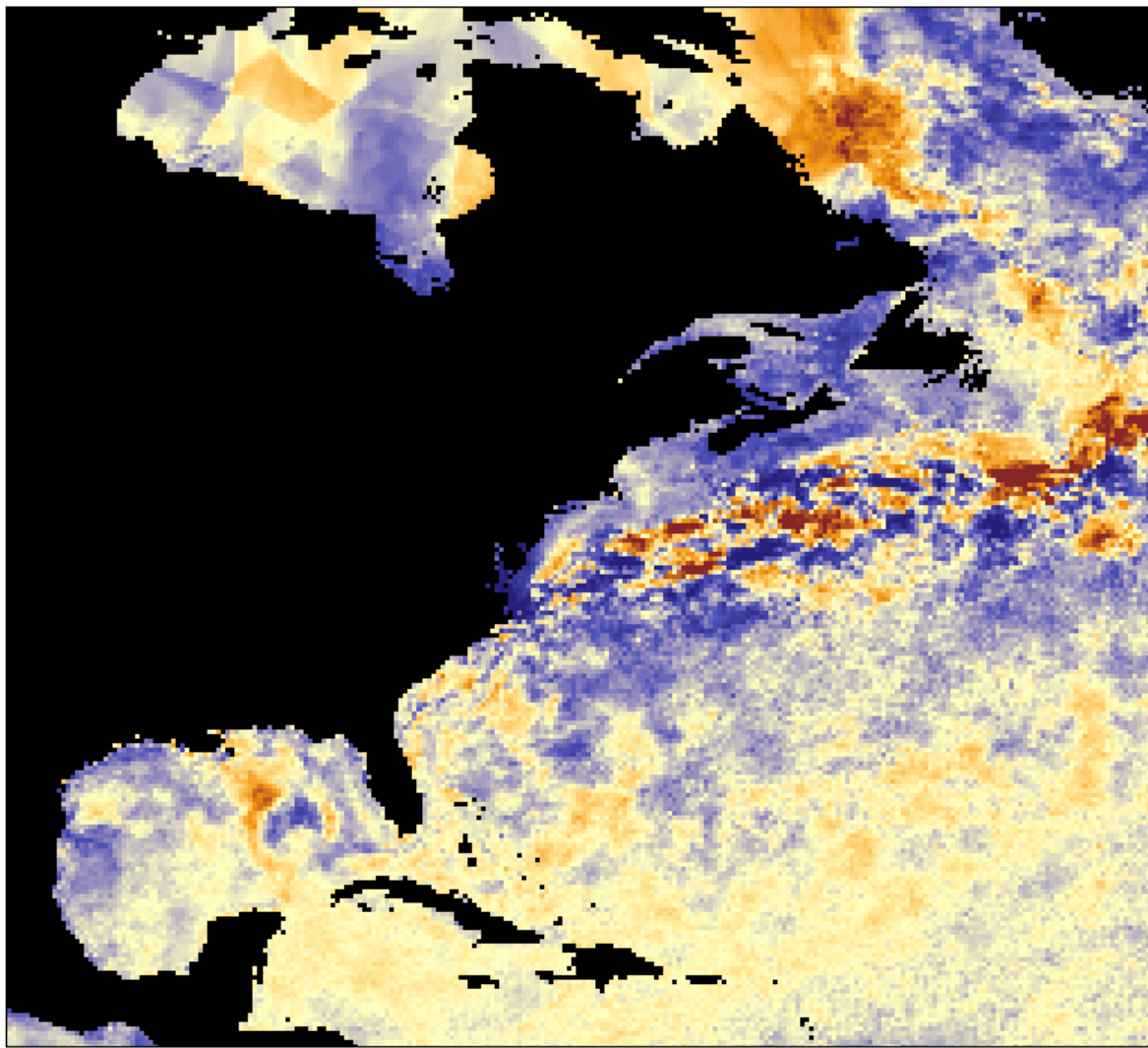


## March NAO v. March SST

P Value

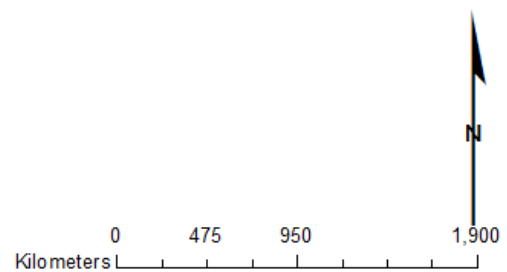
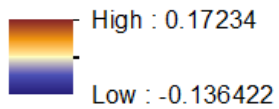


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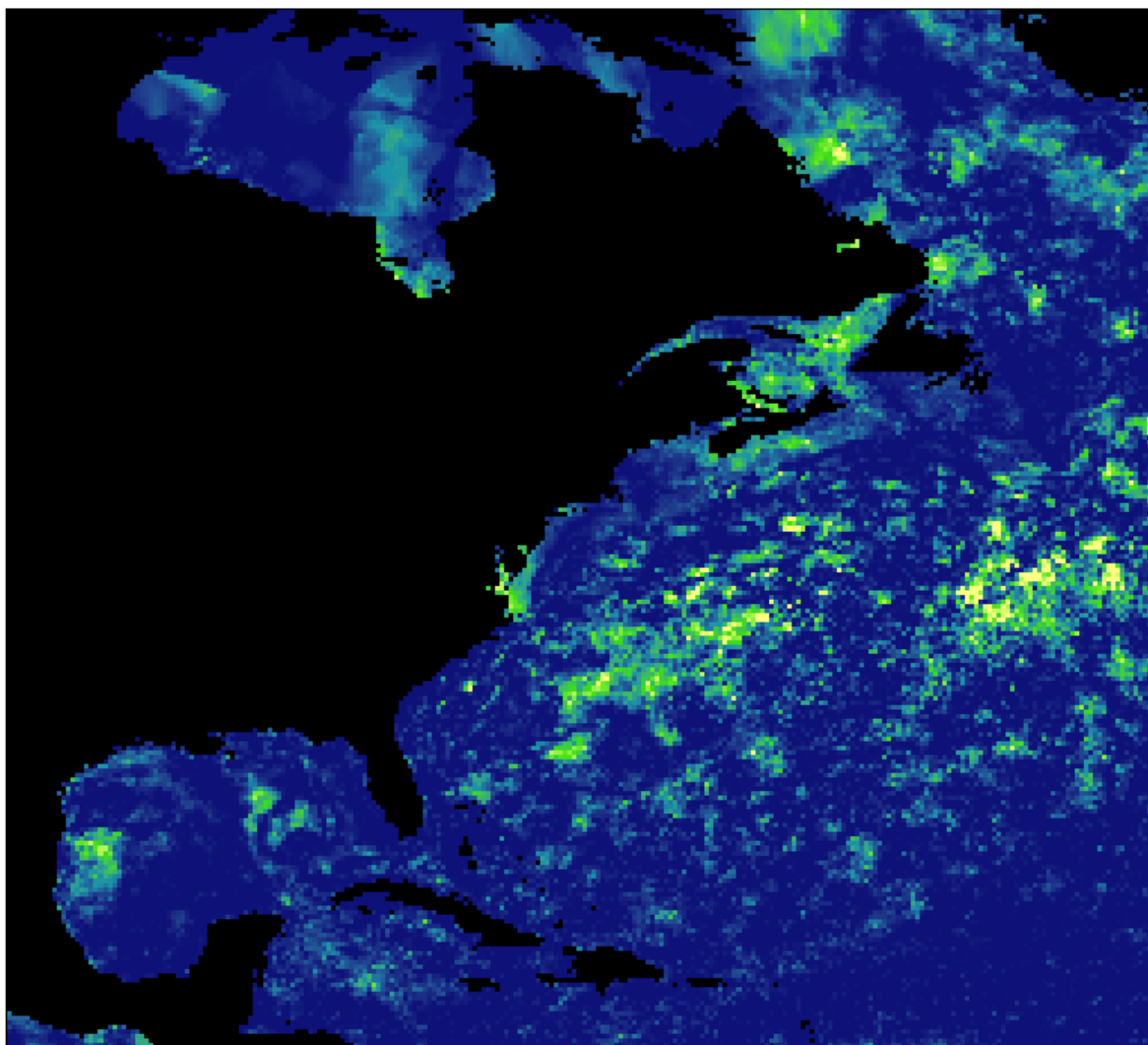


## September NAO v. March SST

Regression Coefficient

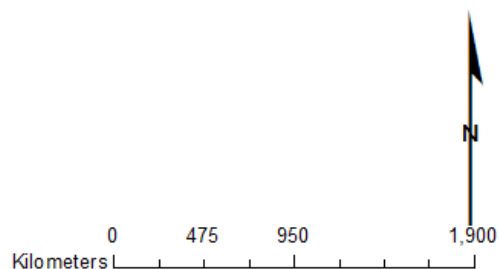
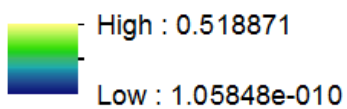


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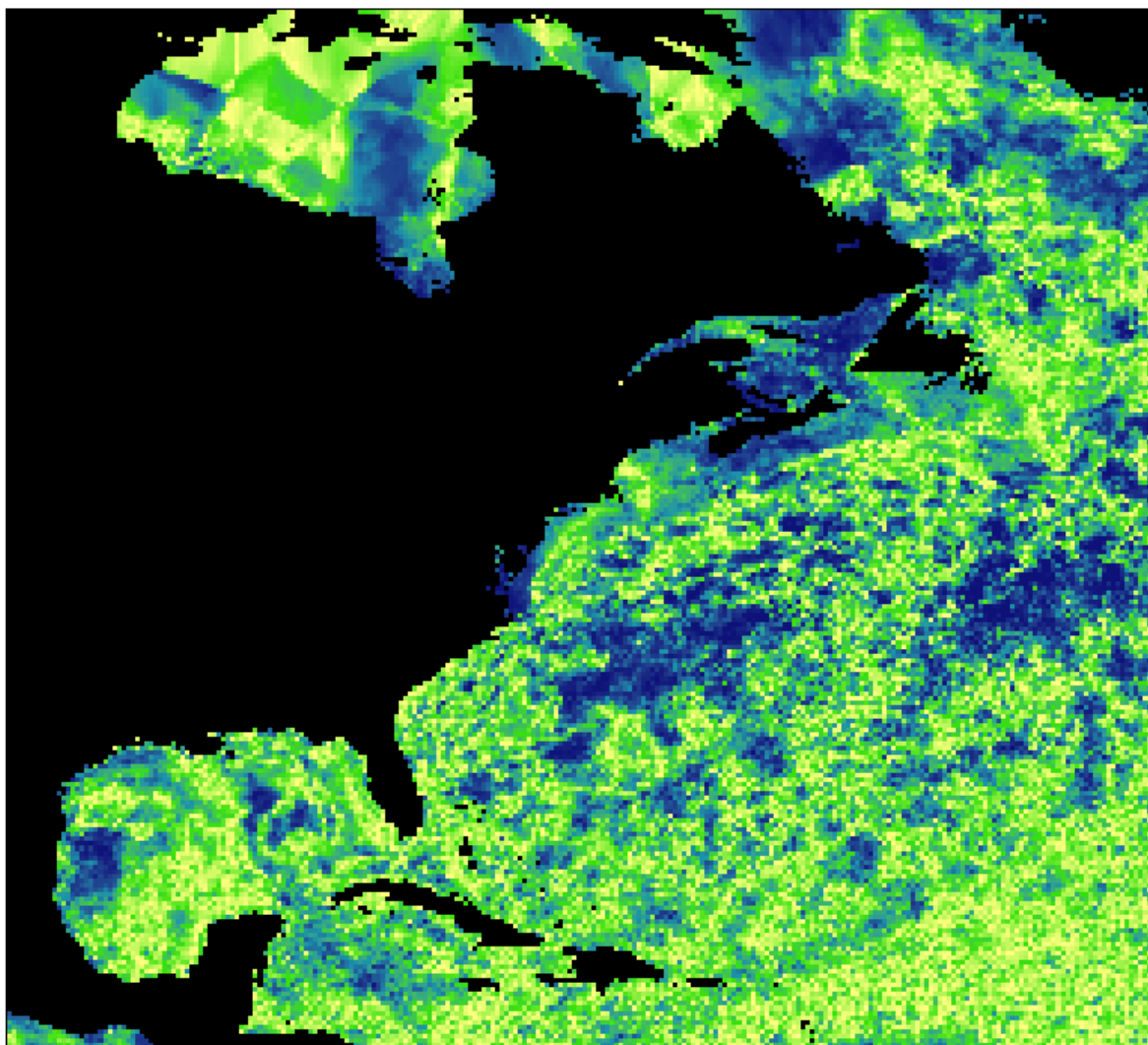


## September NAO v. March SST

R Squared

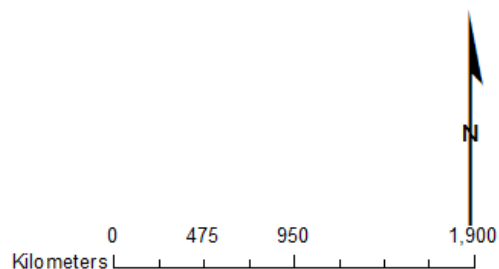
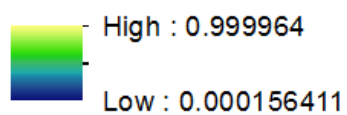


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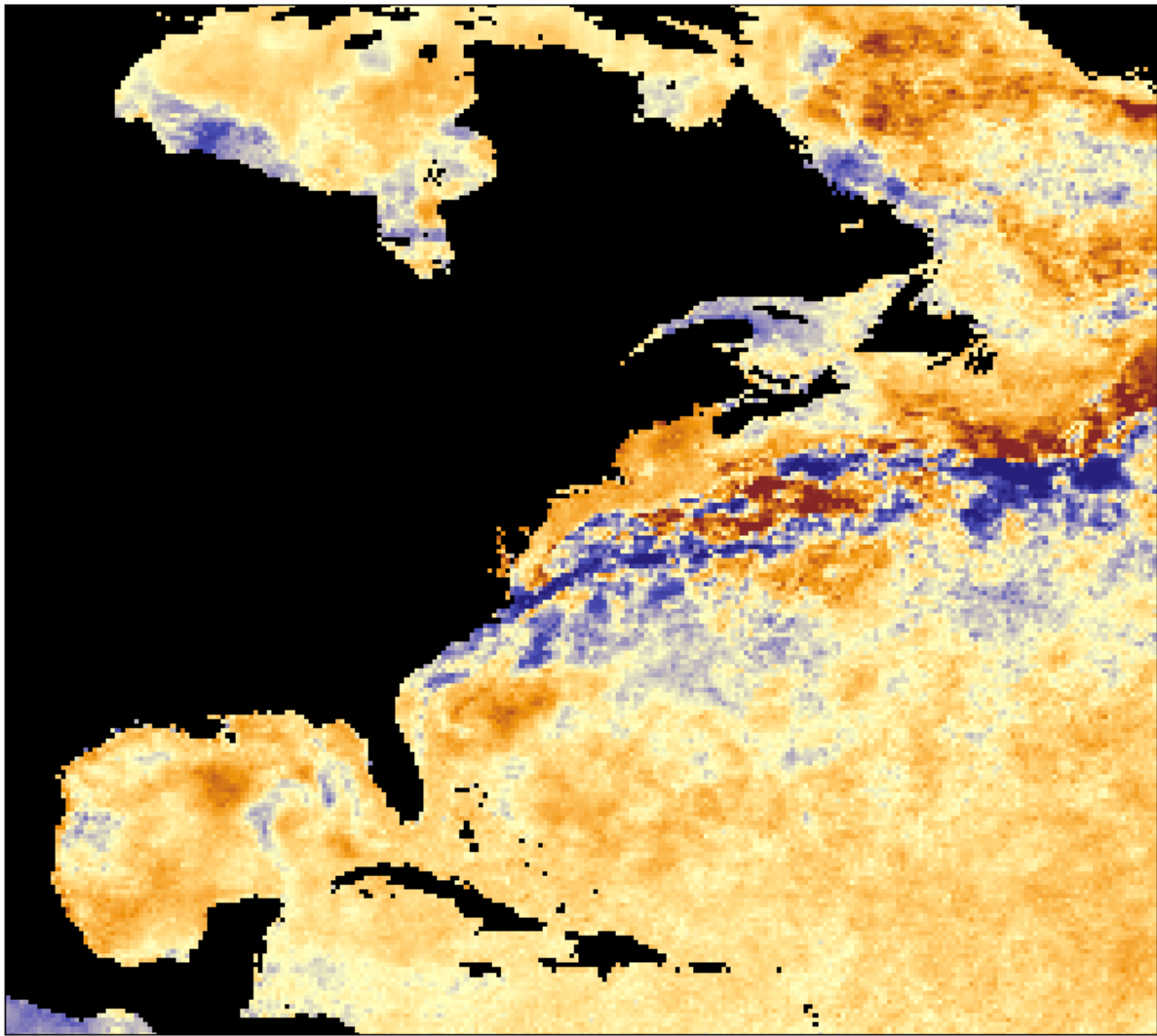


## September NAO v. March SST

P Value



Ana Griefen 2014  
WGS 1984



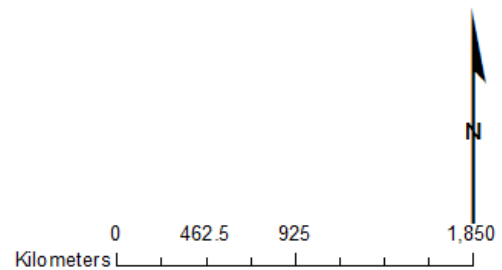
## April NAO v. April SST

Regression Coefficient

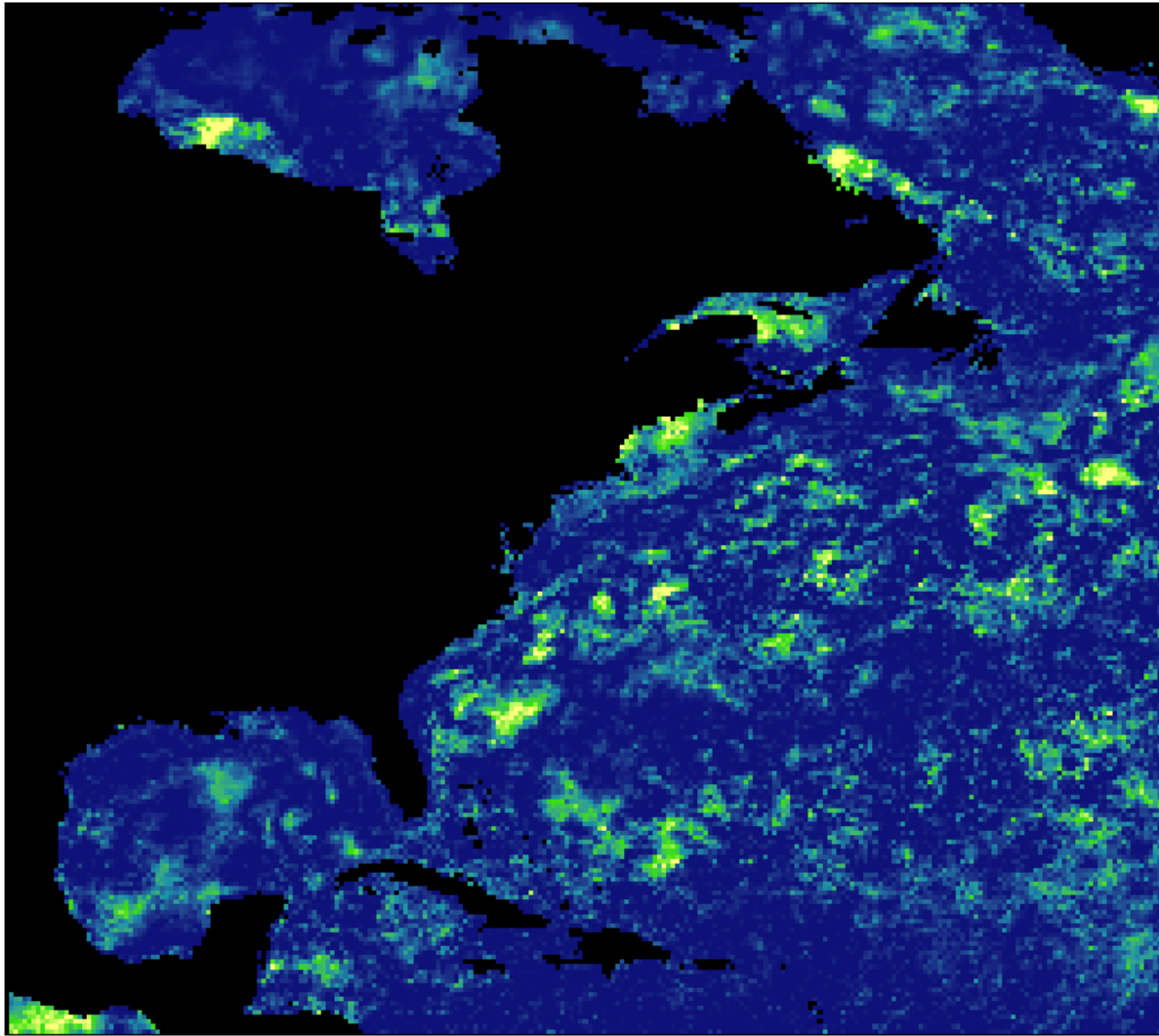


High : 0.136965

Low : -0.15249

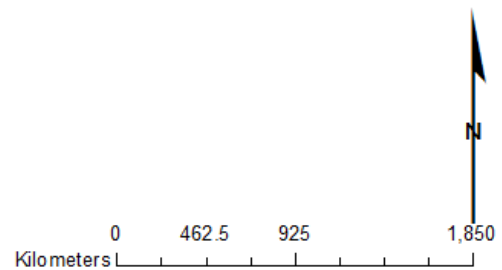


Ana Griefen 2014  
WGS 1984



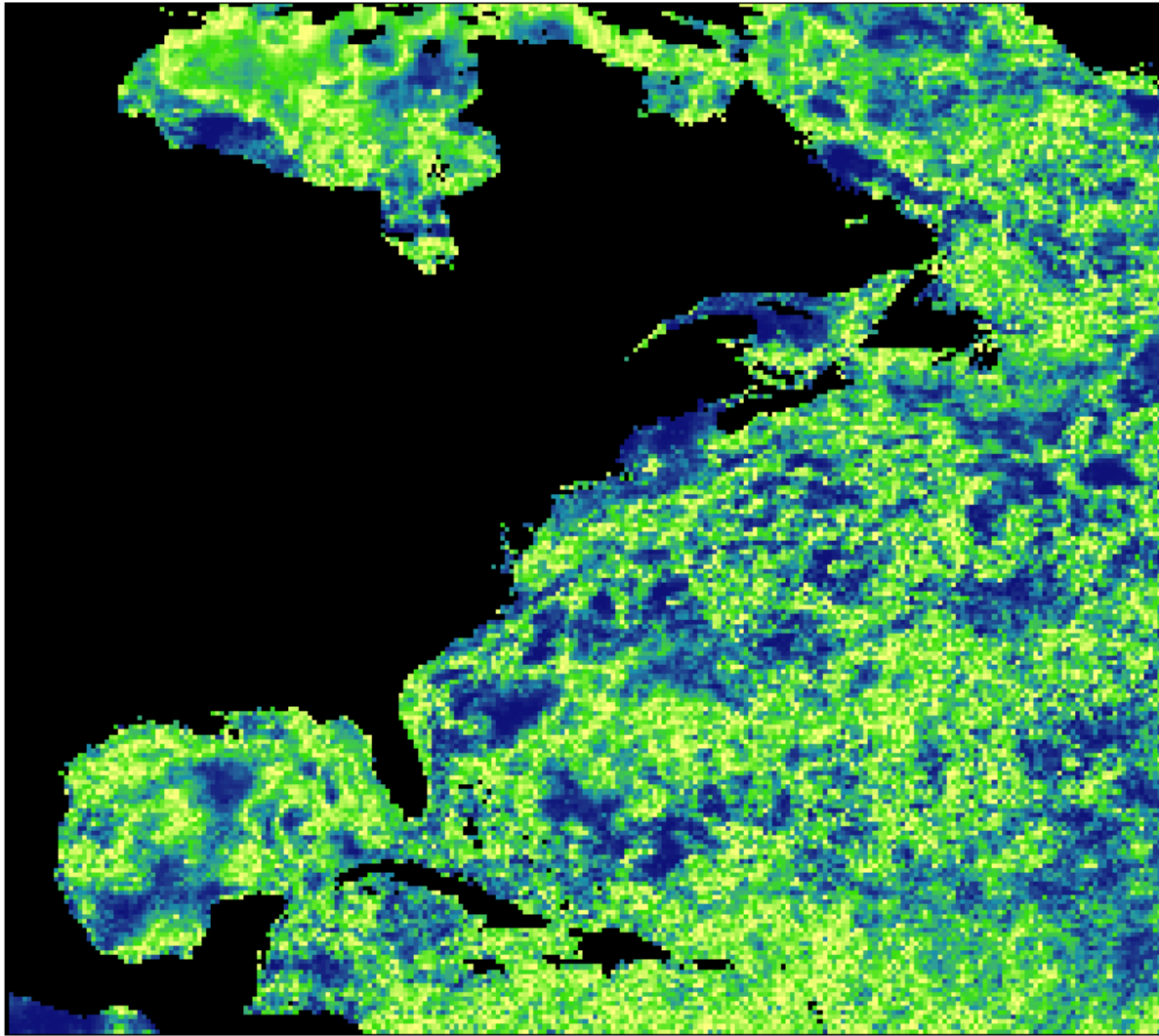
## April NAO v. April SST

R Squared



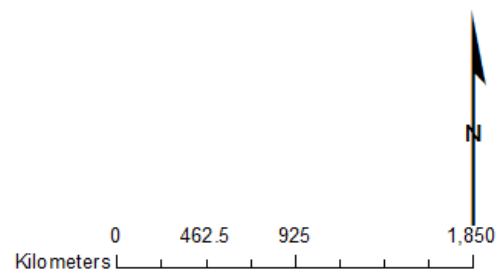
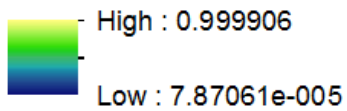
Ana Griefen 2014  
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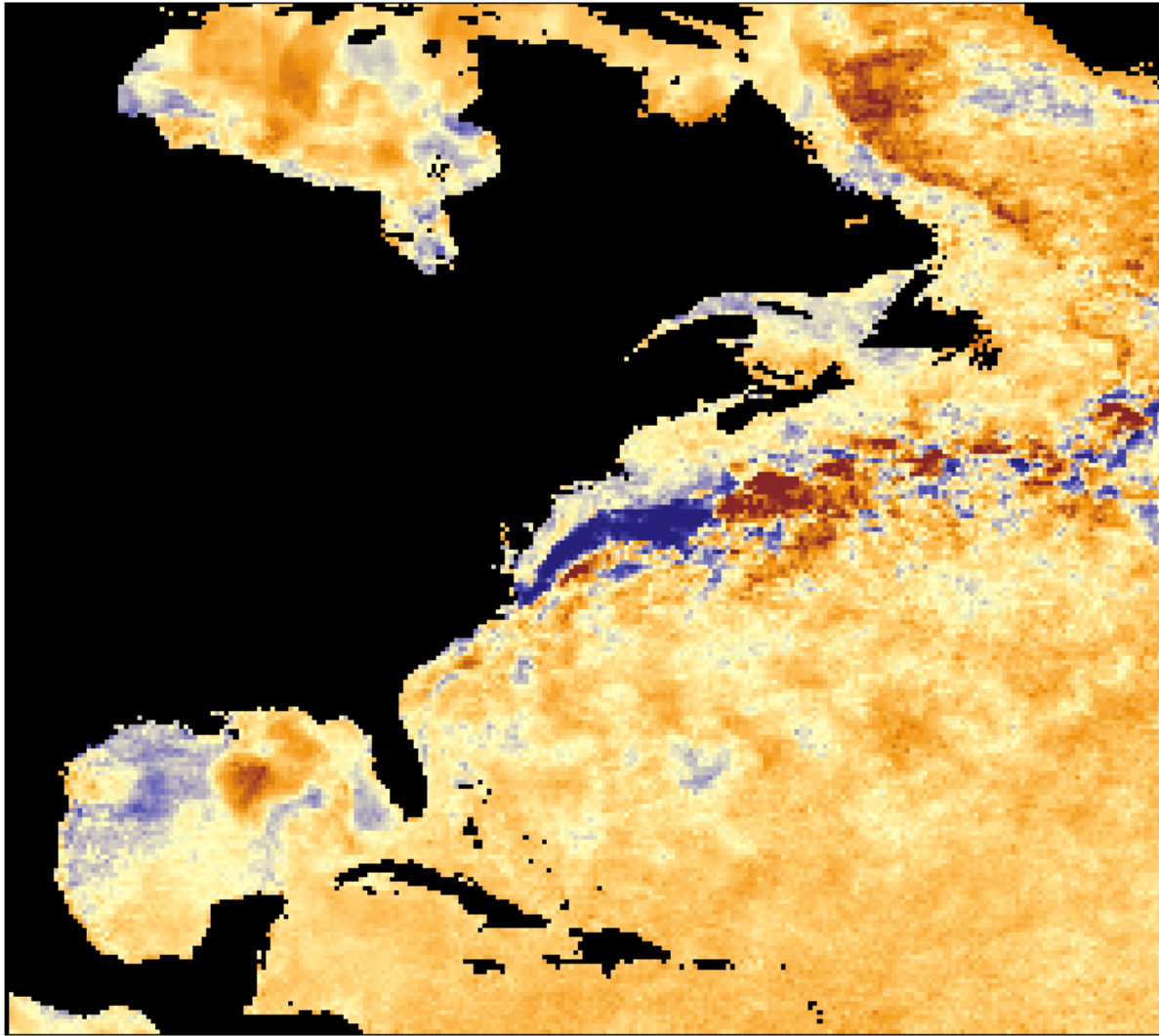
## April NAO v. April SST

P Value



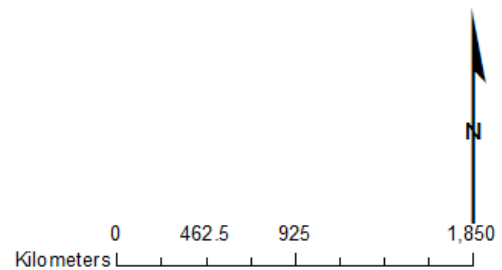
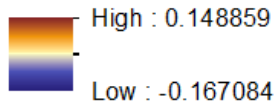
Ana Griefen 2014  
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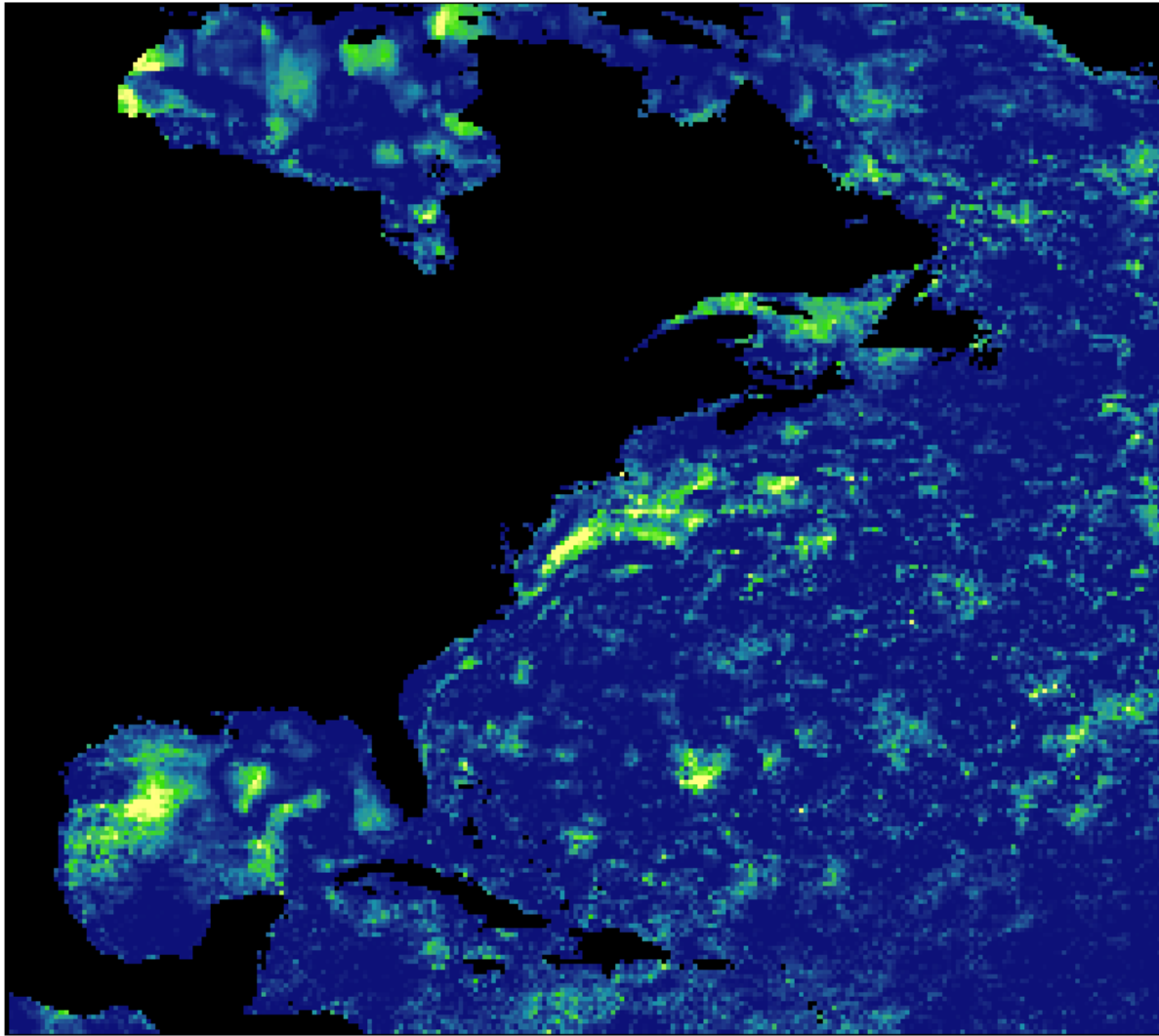


## October NAO v. April SST

Regression Coefficient

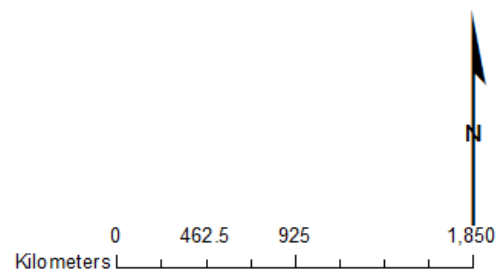
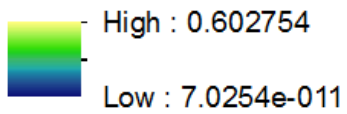


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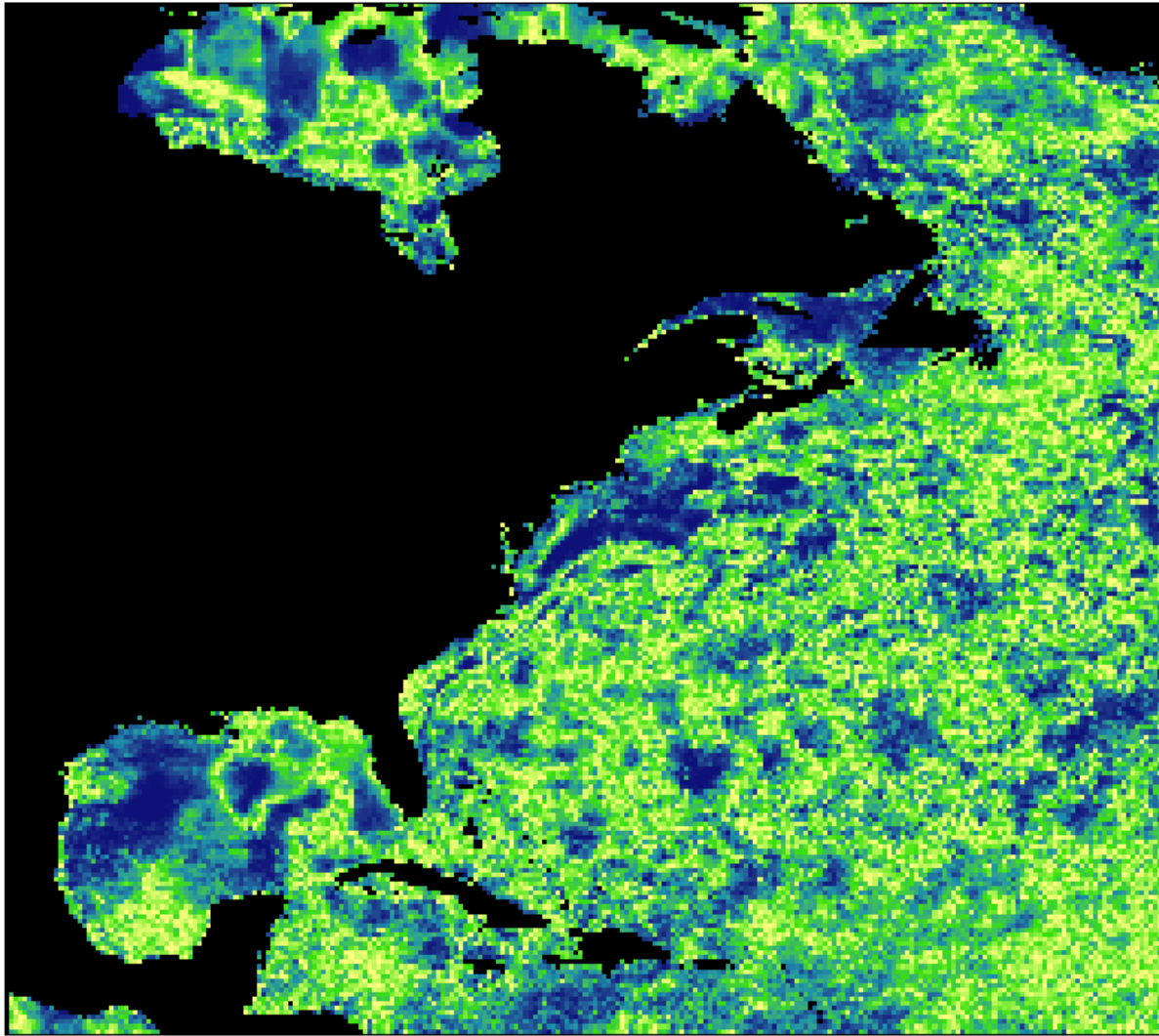


## October NAO v. April SST

R Squared

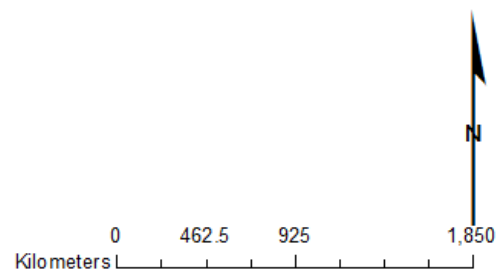
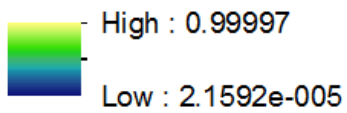


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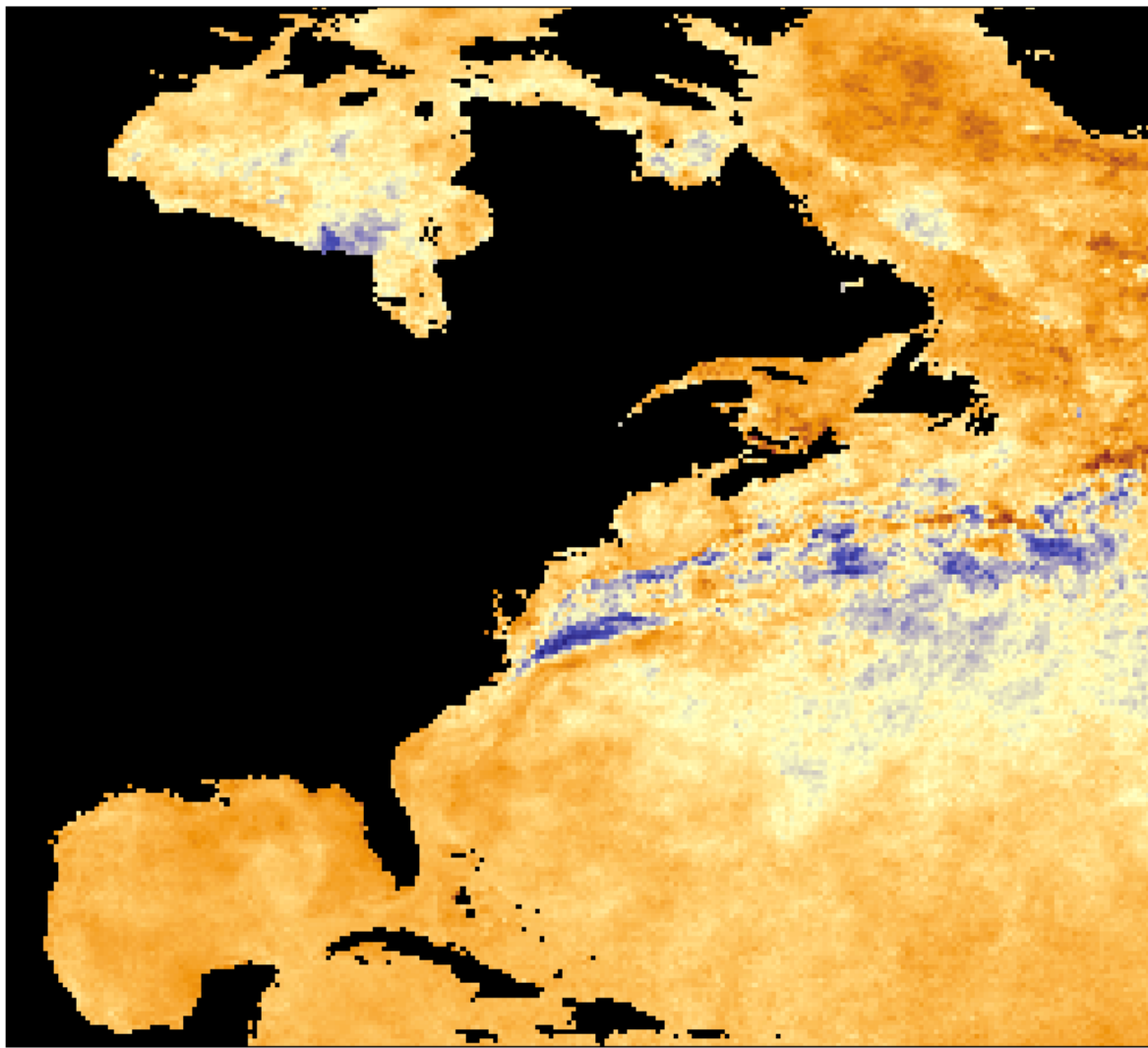


## October NAO v. April SST

P Value

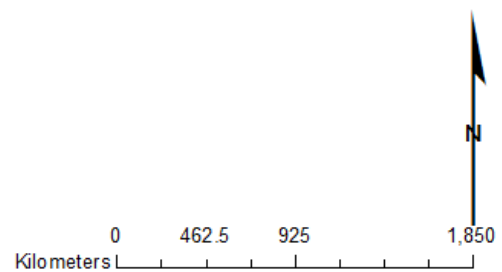
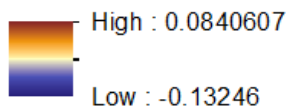


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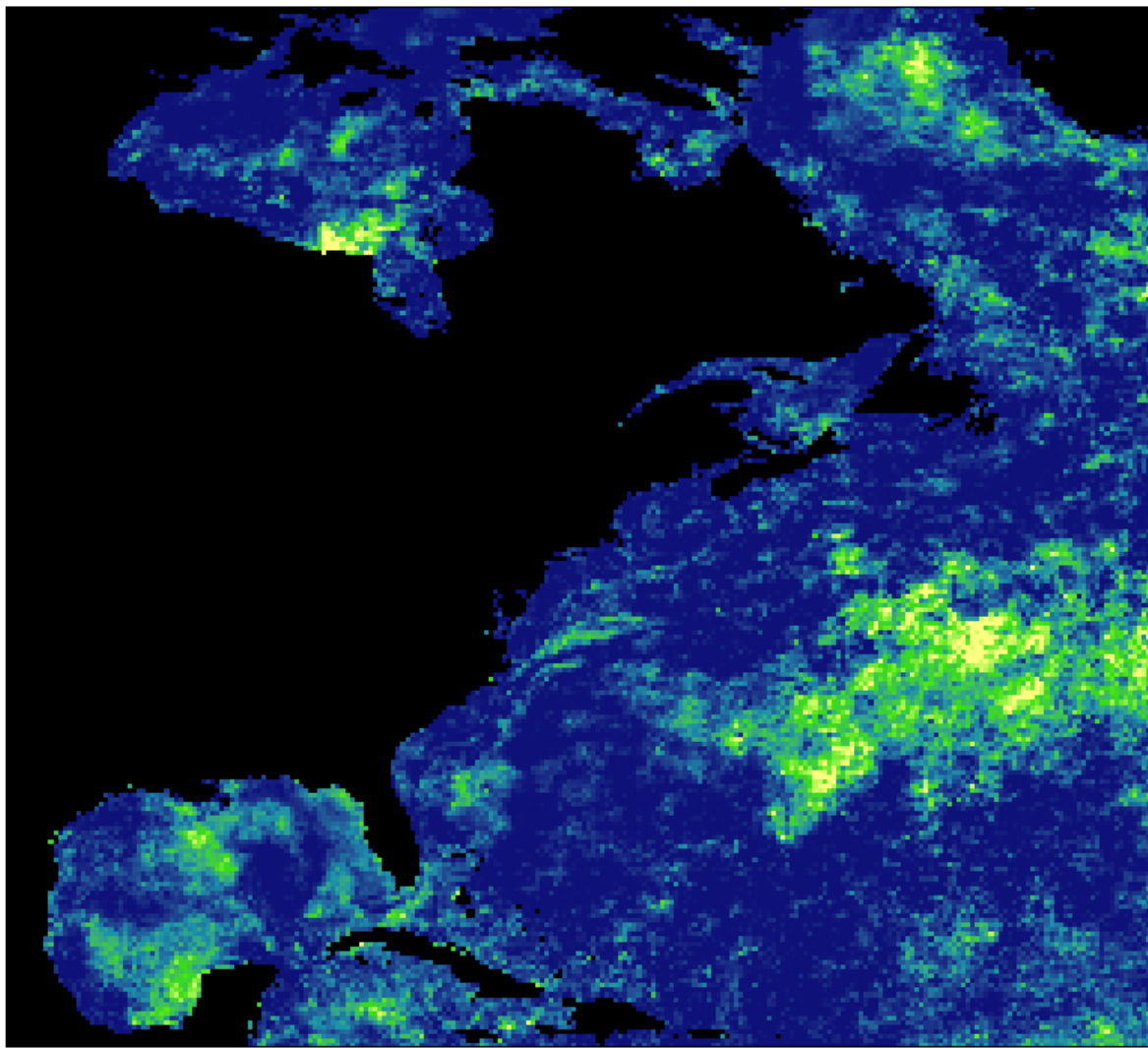


## May NAO v. May SST

Regression Coefficient

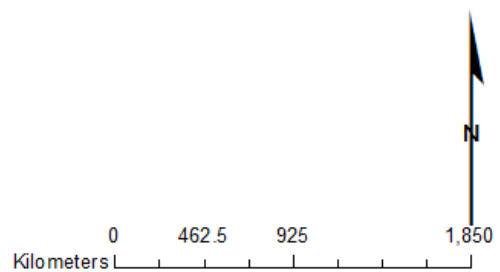
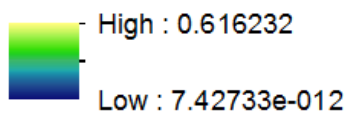


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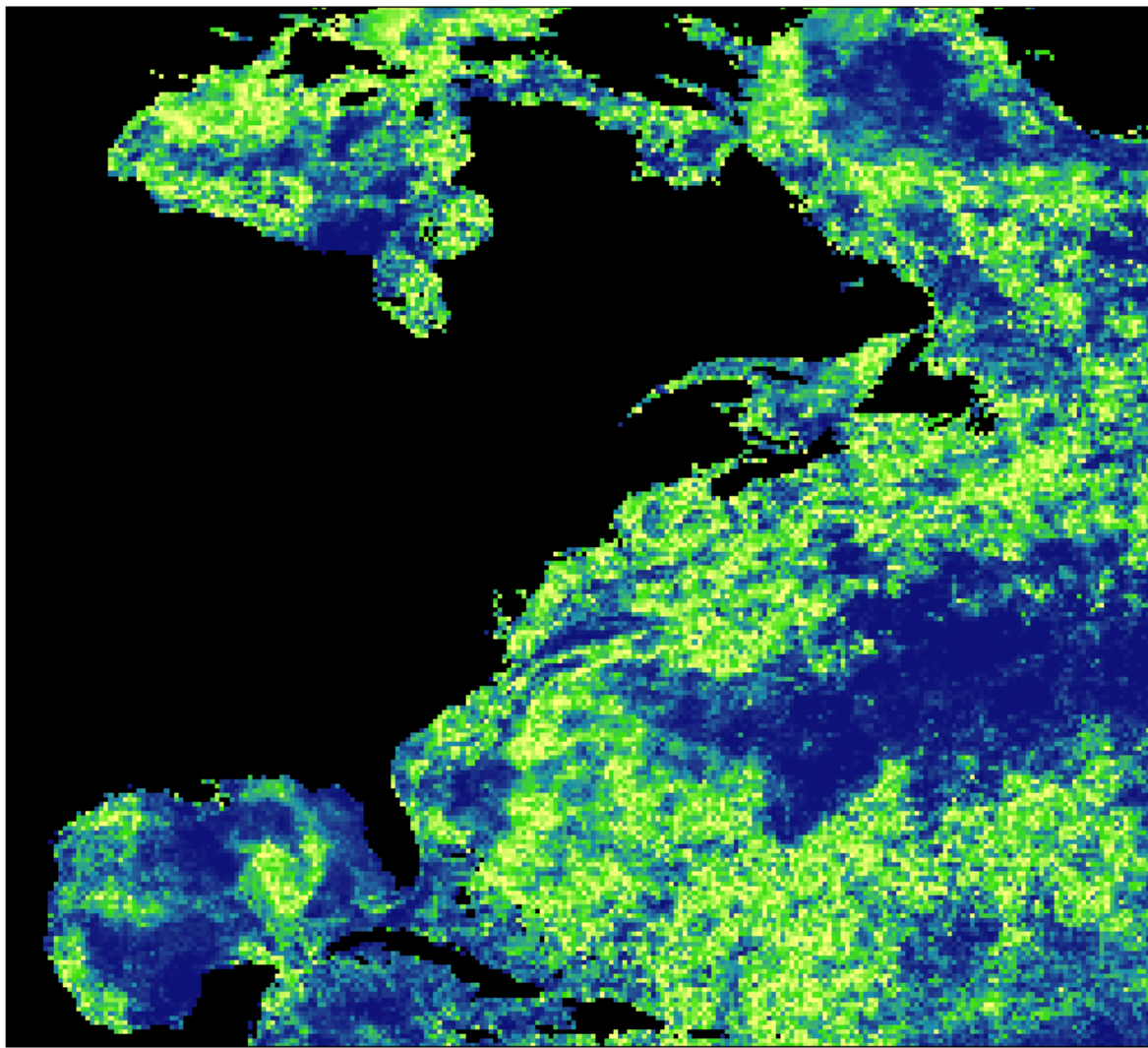


## May NAO v. May SST

R Squared

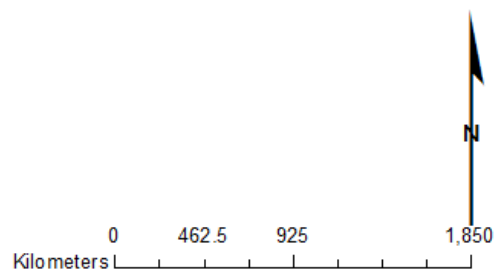
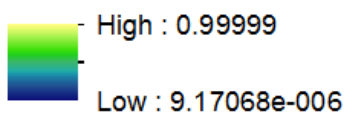


Ana Griefen 2014  
WGS 1984

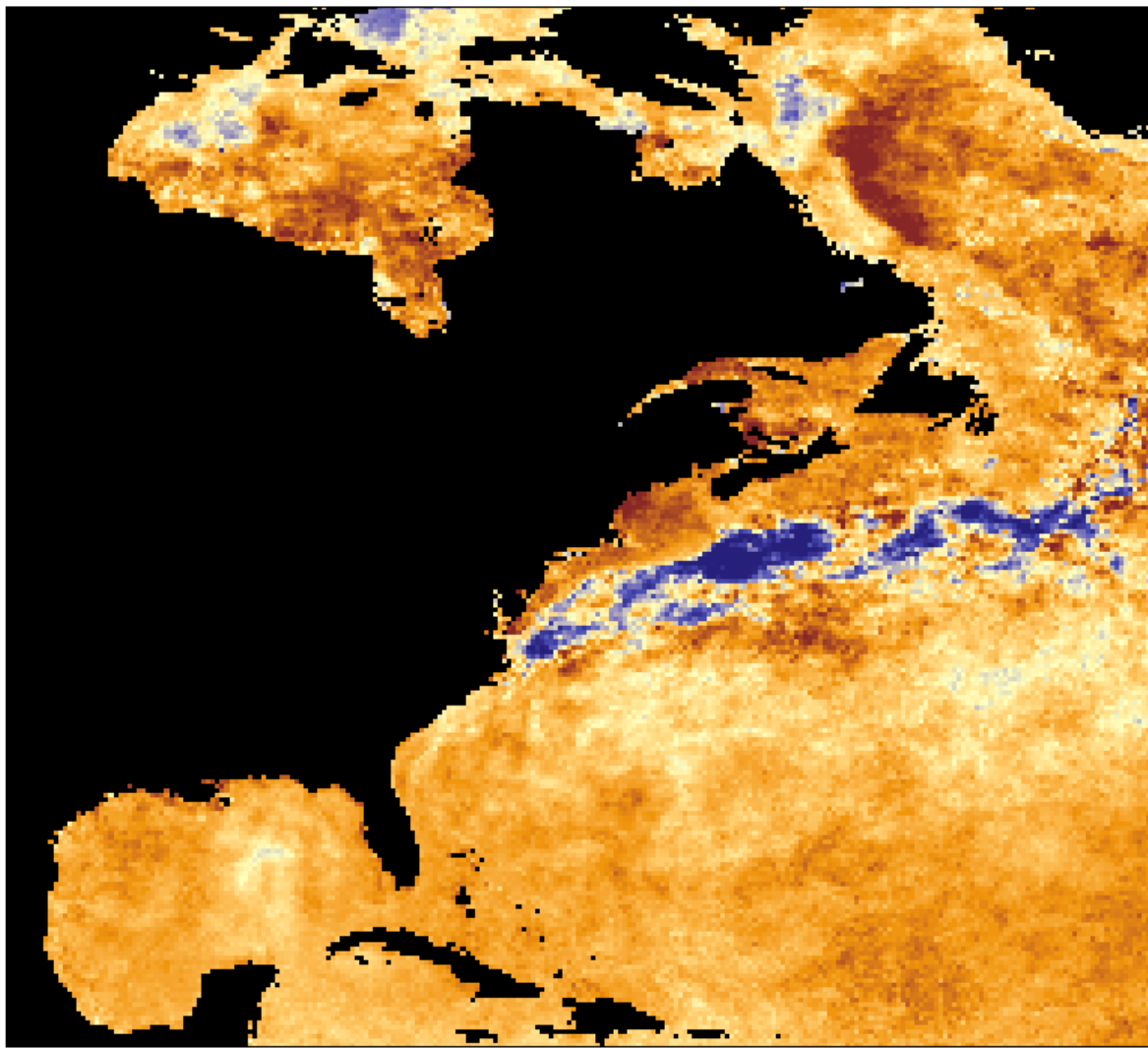


## May NAO v. May SST

P Value

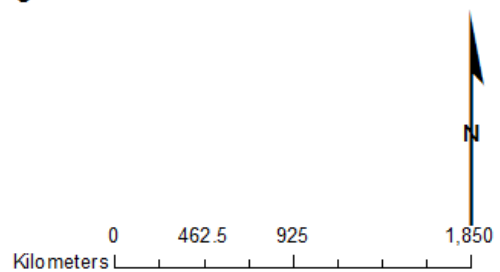
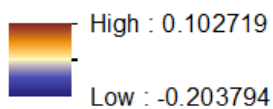


Ana Griefen 2014  
WGS 1984



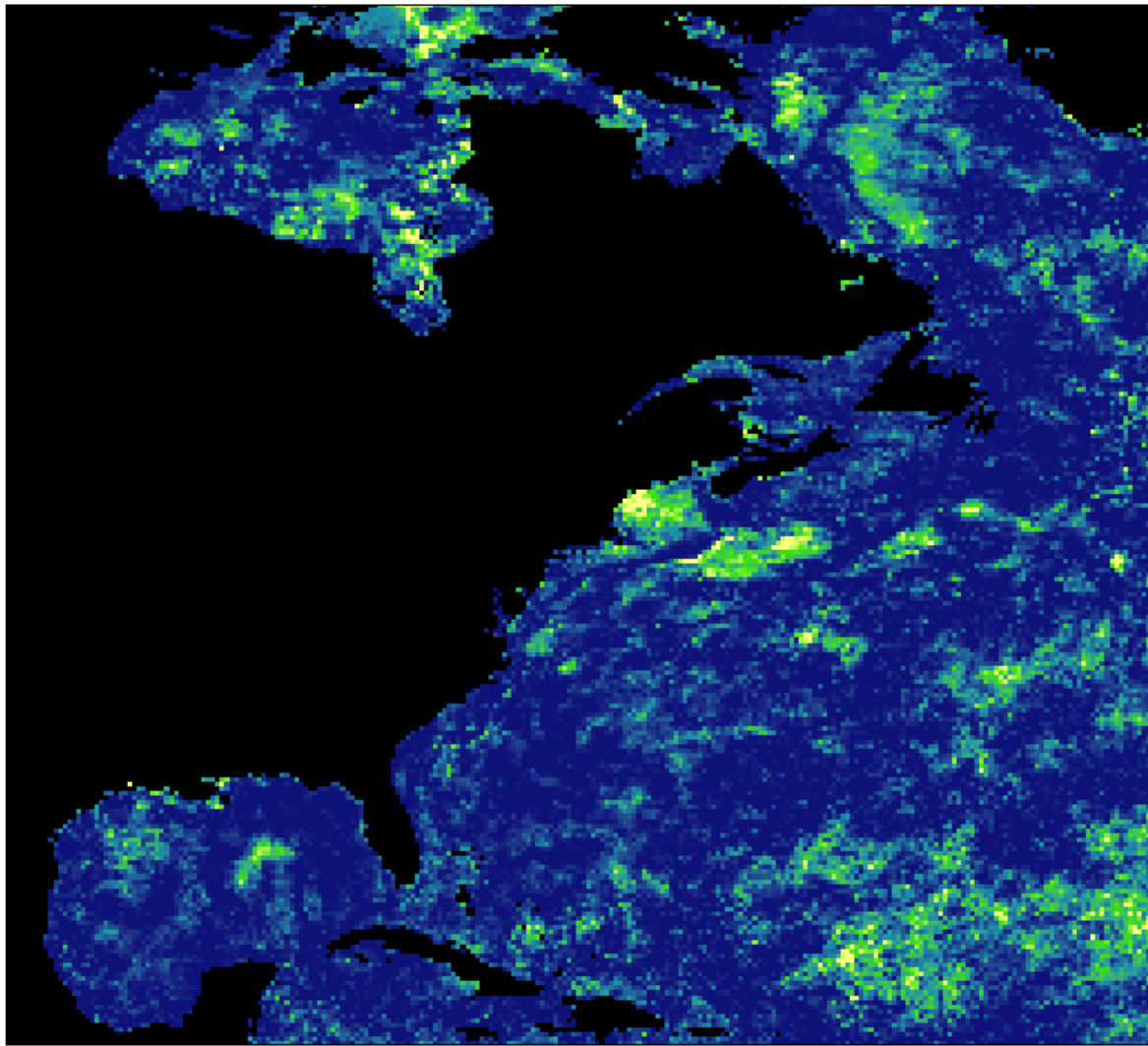
## November NAO v. May SST

Regression Coefficient



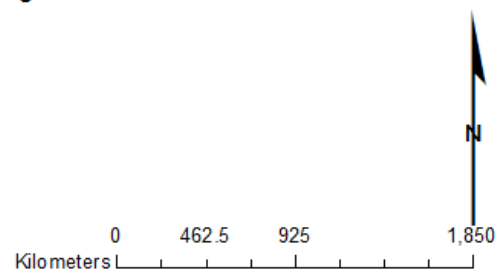
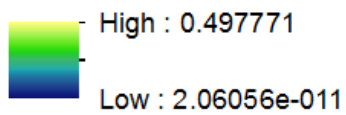
Ana Griefen 2014  
WGS 1984





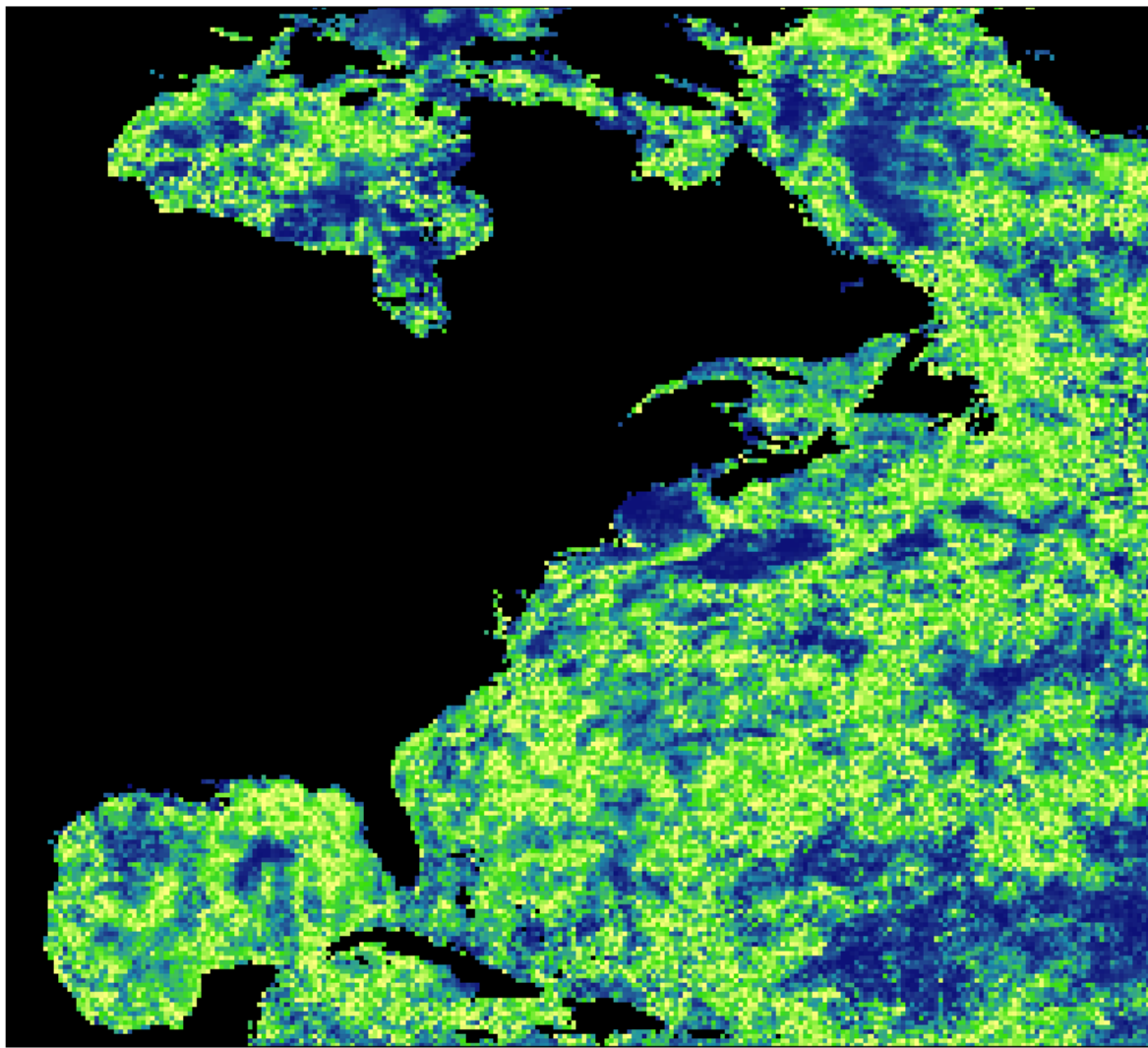
## November NAO v. May SST

R Squared



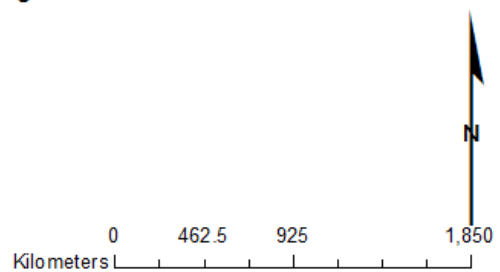
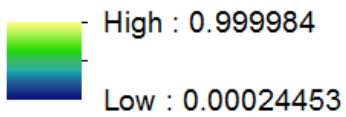
Ana Griefen 2014  
WGS 1984



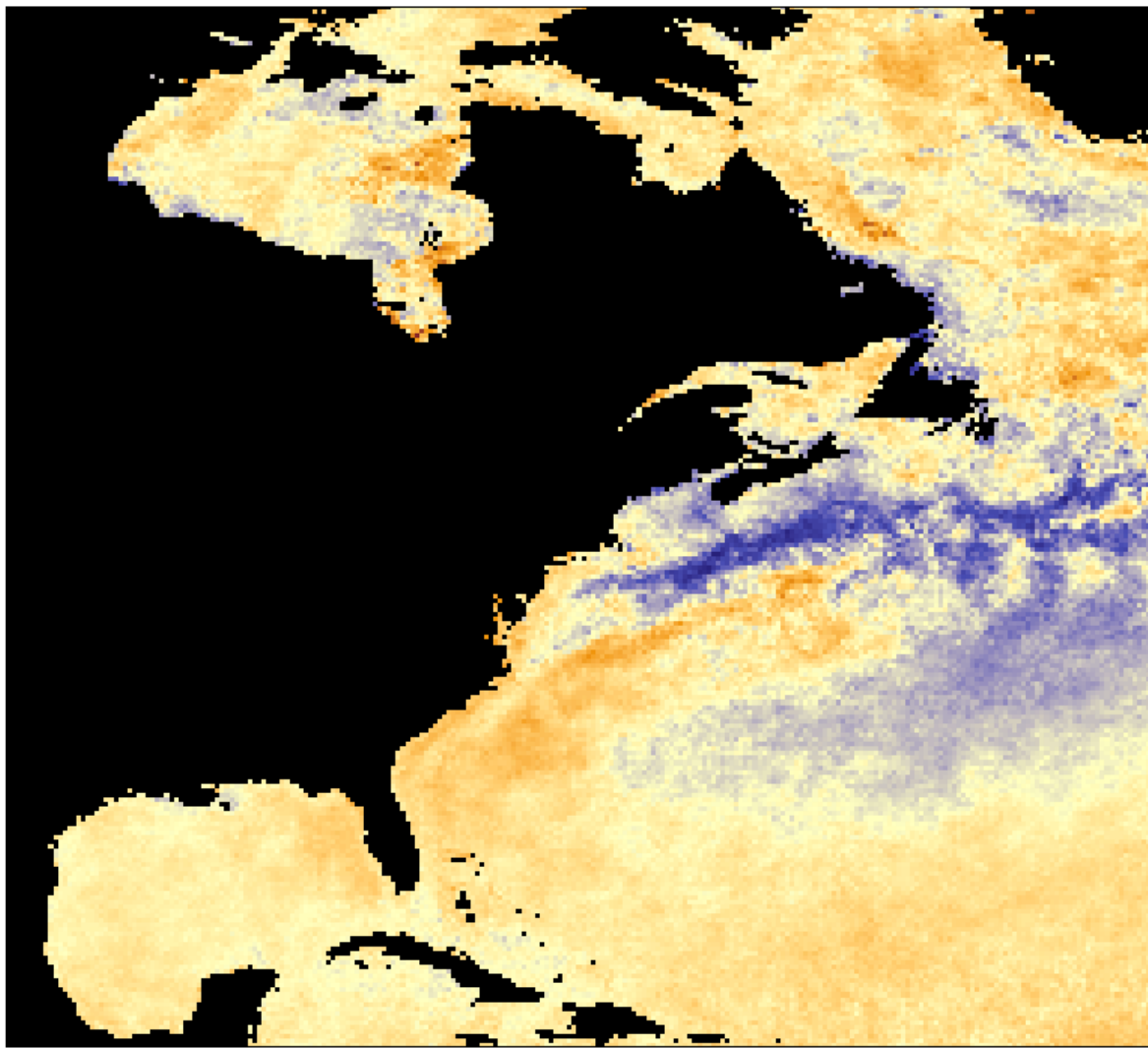


## November NAO v. May SST

P Value

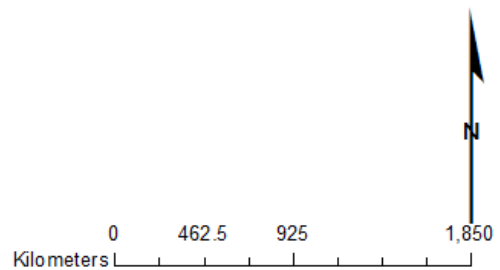
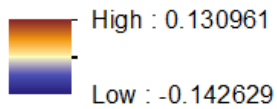


Ana Griefen 2014  
WGS 1984

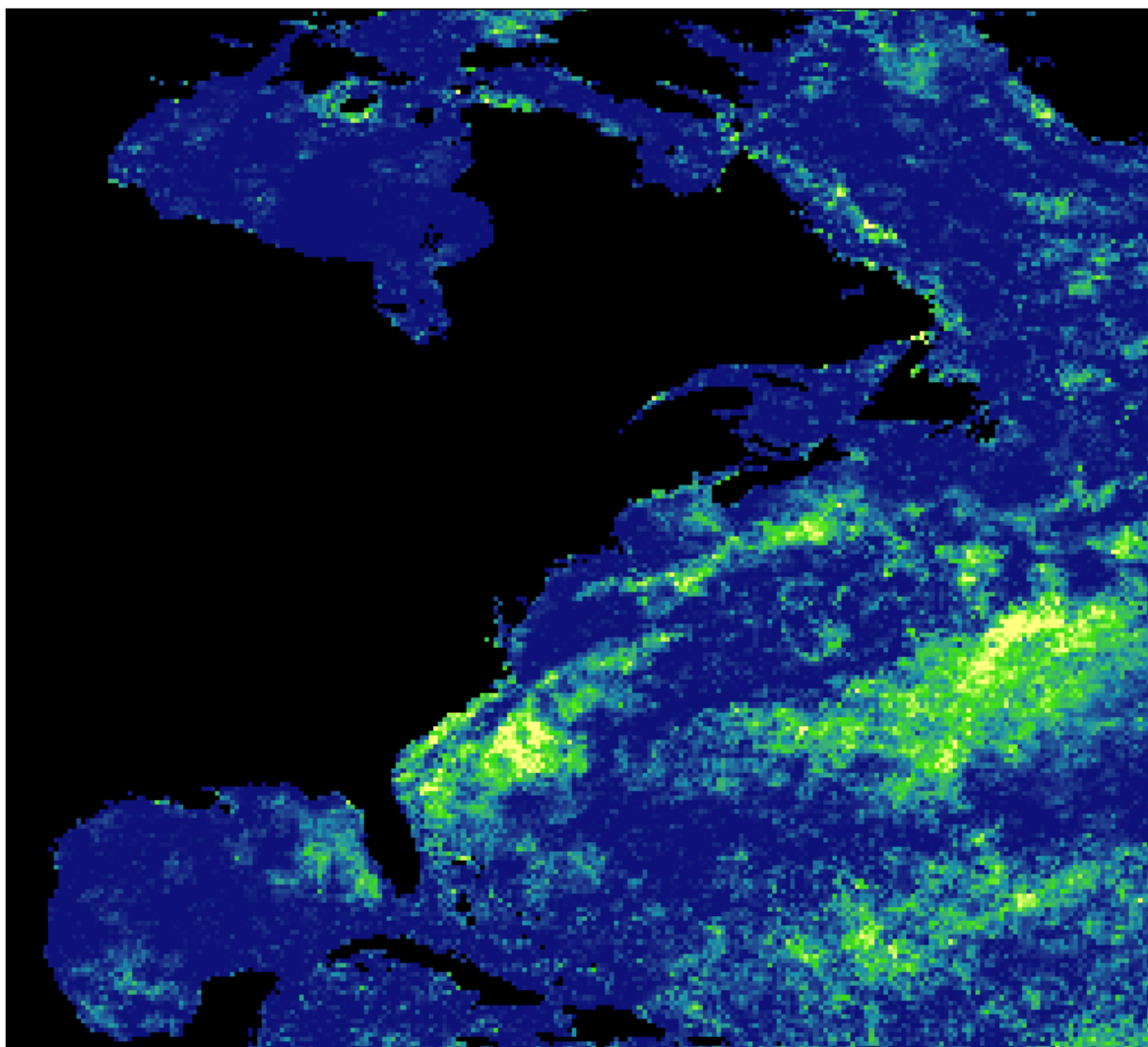


## June NAO v. June SST

Regression Coefficient

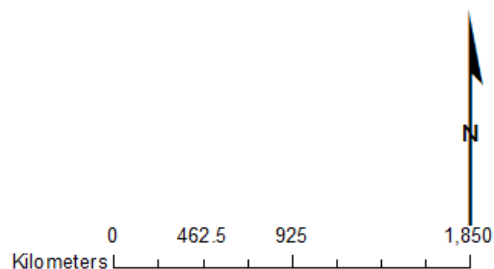
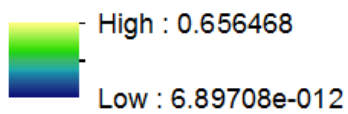


Ana Griefen 2014  
WGS 1984

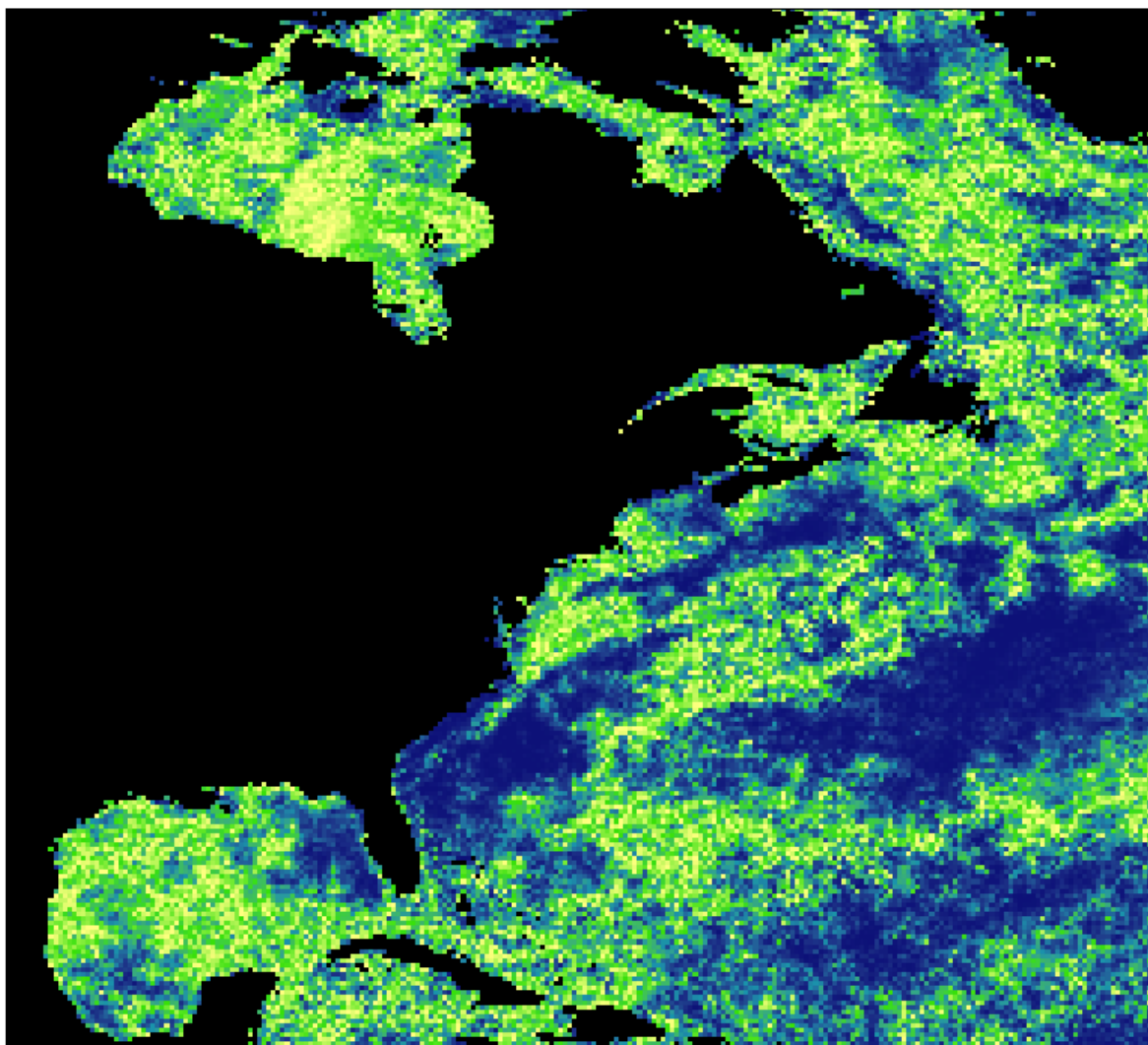


## June NAO v. June SST

R Squared

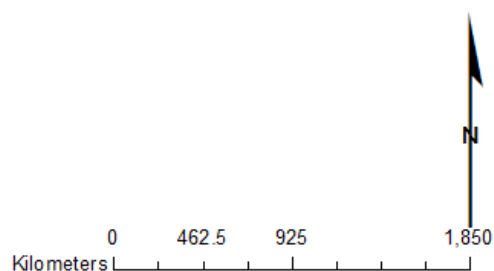
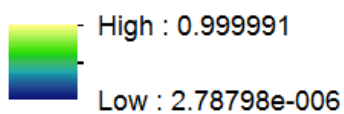


Ana Griefen 2014  
WGS 1984

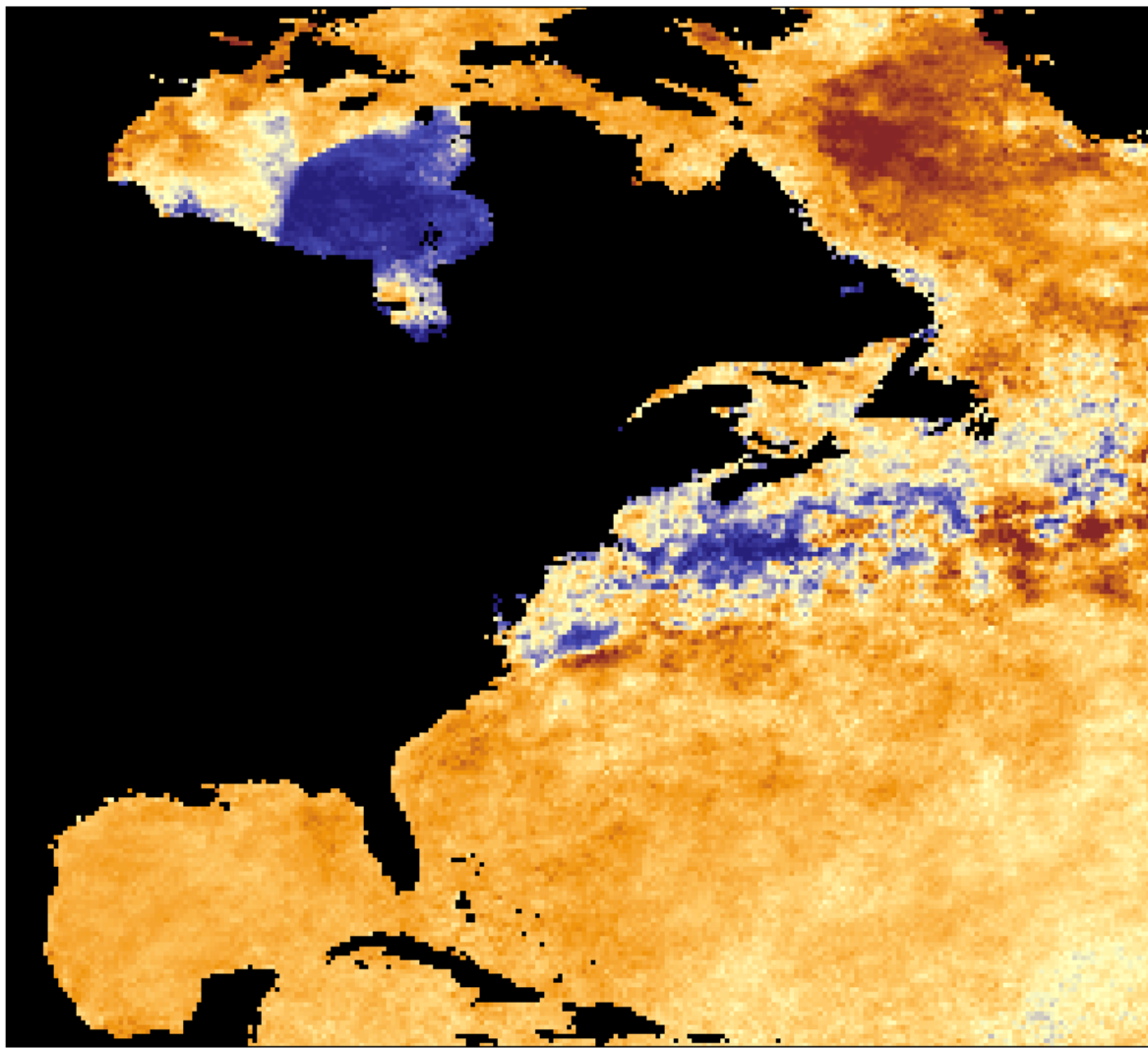


## June NAO v. June SST

P Value

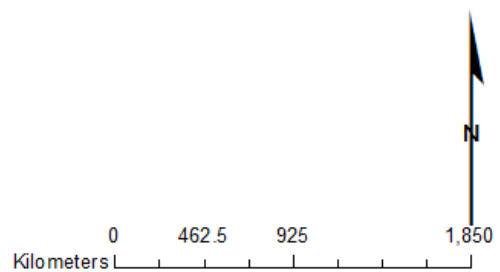
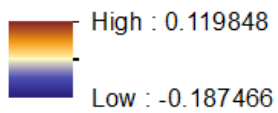


Ana Griefen 2014  
WGS 1984

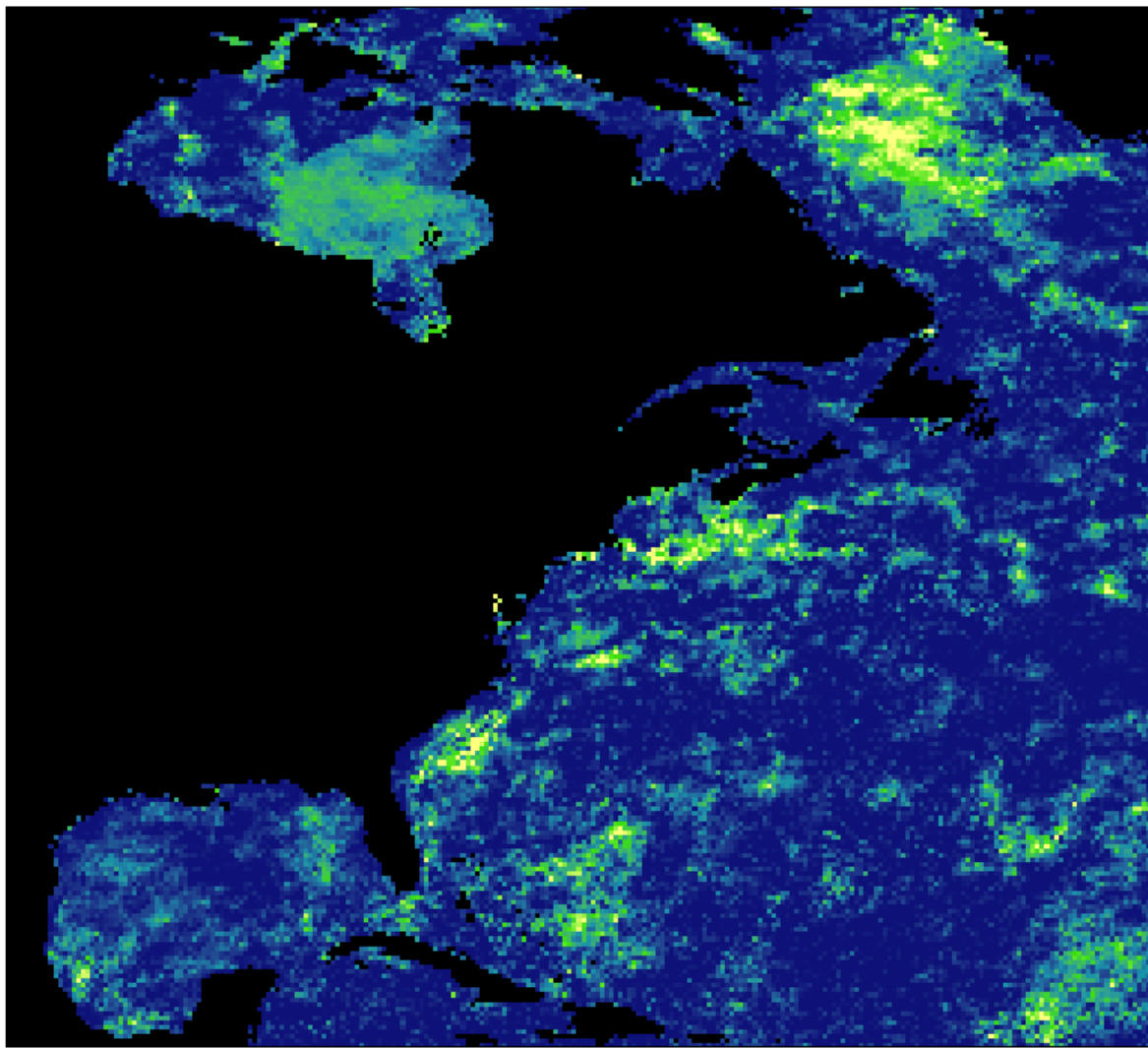


## Dec NAO v. June SST

Regression Coefficient

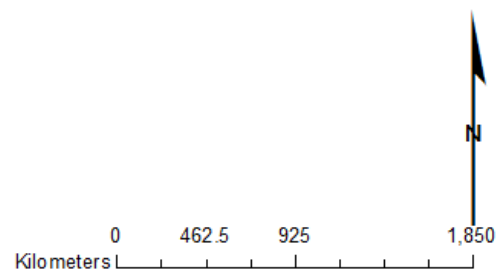
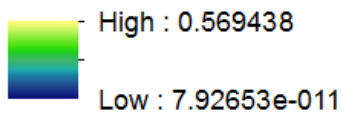


Ana Griefen 2014  
WGS 1984

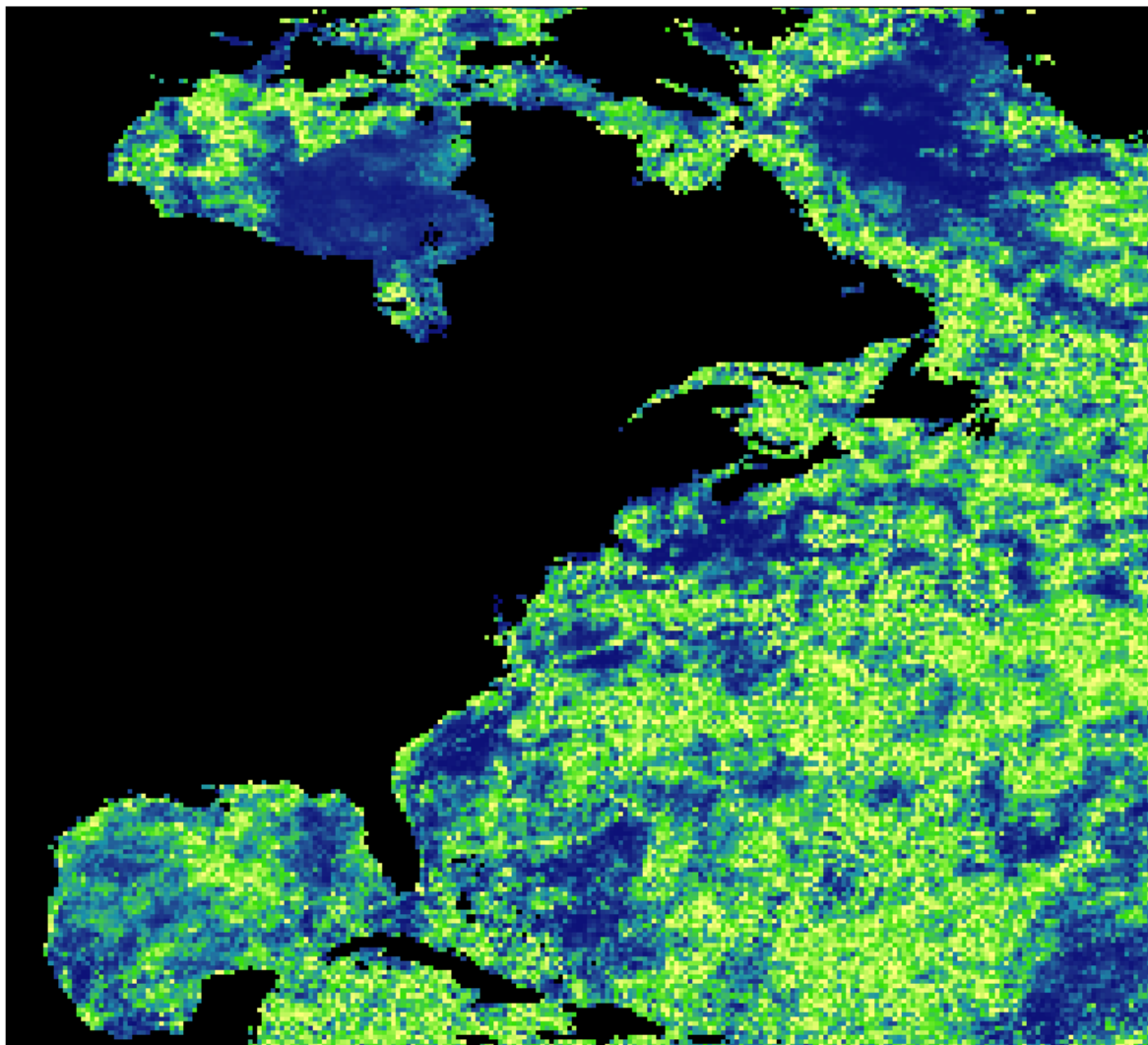


## Dec NAO v. June SST

R Squared

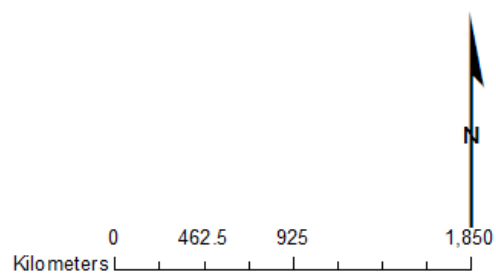
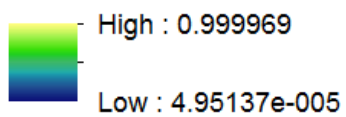


Ana Griefen 2014  
WGS 1984



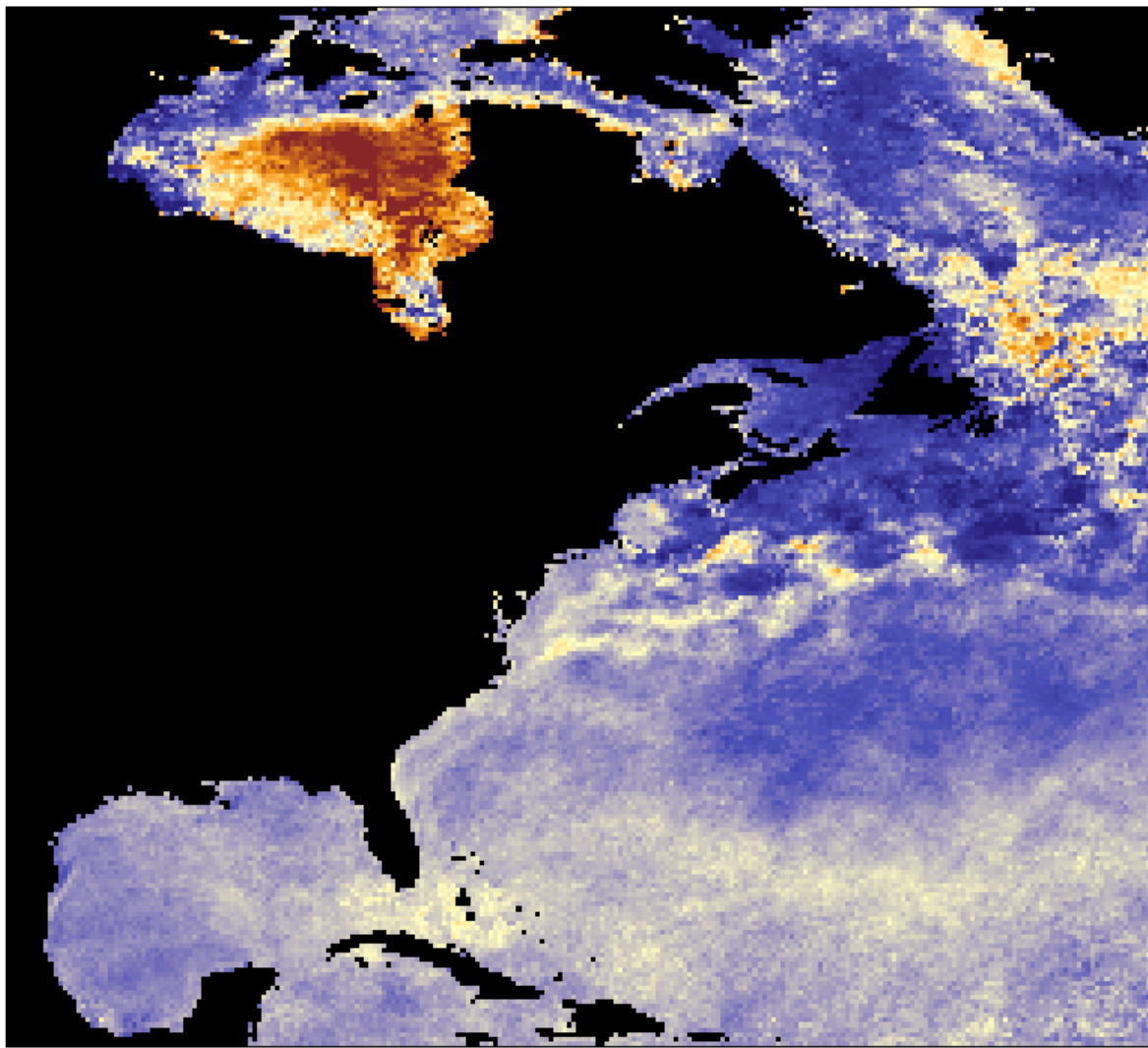
## Dec NAO v. June SST

P Value



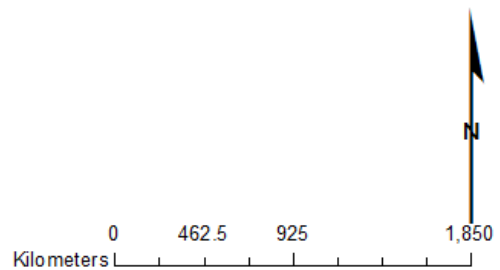
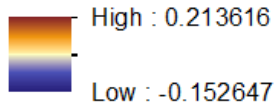
Ana Griefen 2014  
WGS 1984





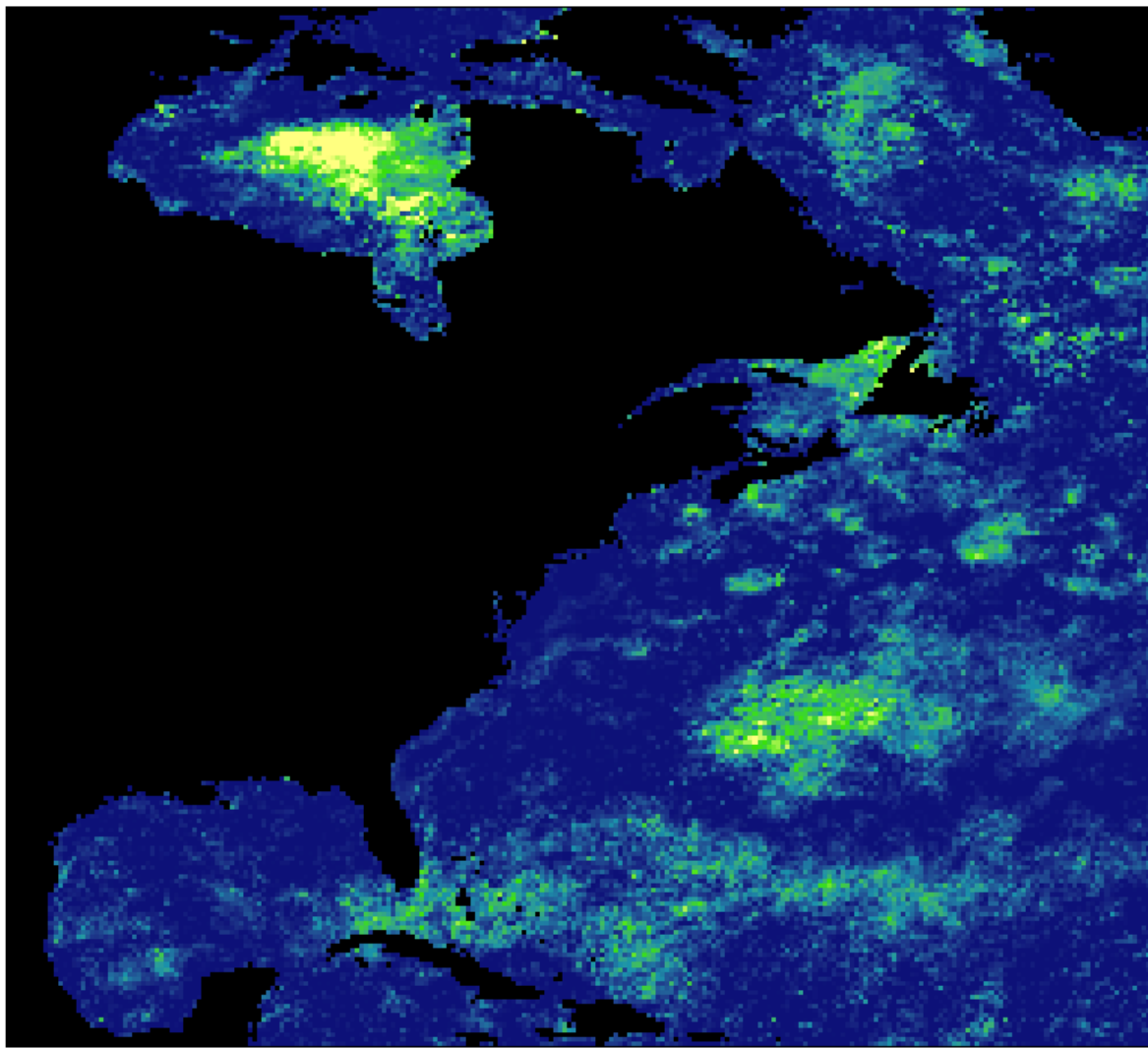
## July NAO v. July SST

Regression Coefficient



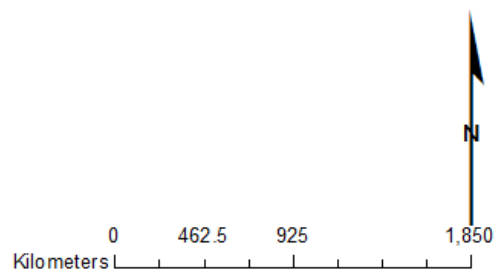
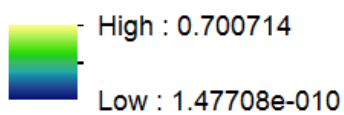
Ana Griefen 2014  
WGS 1984



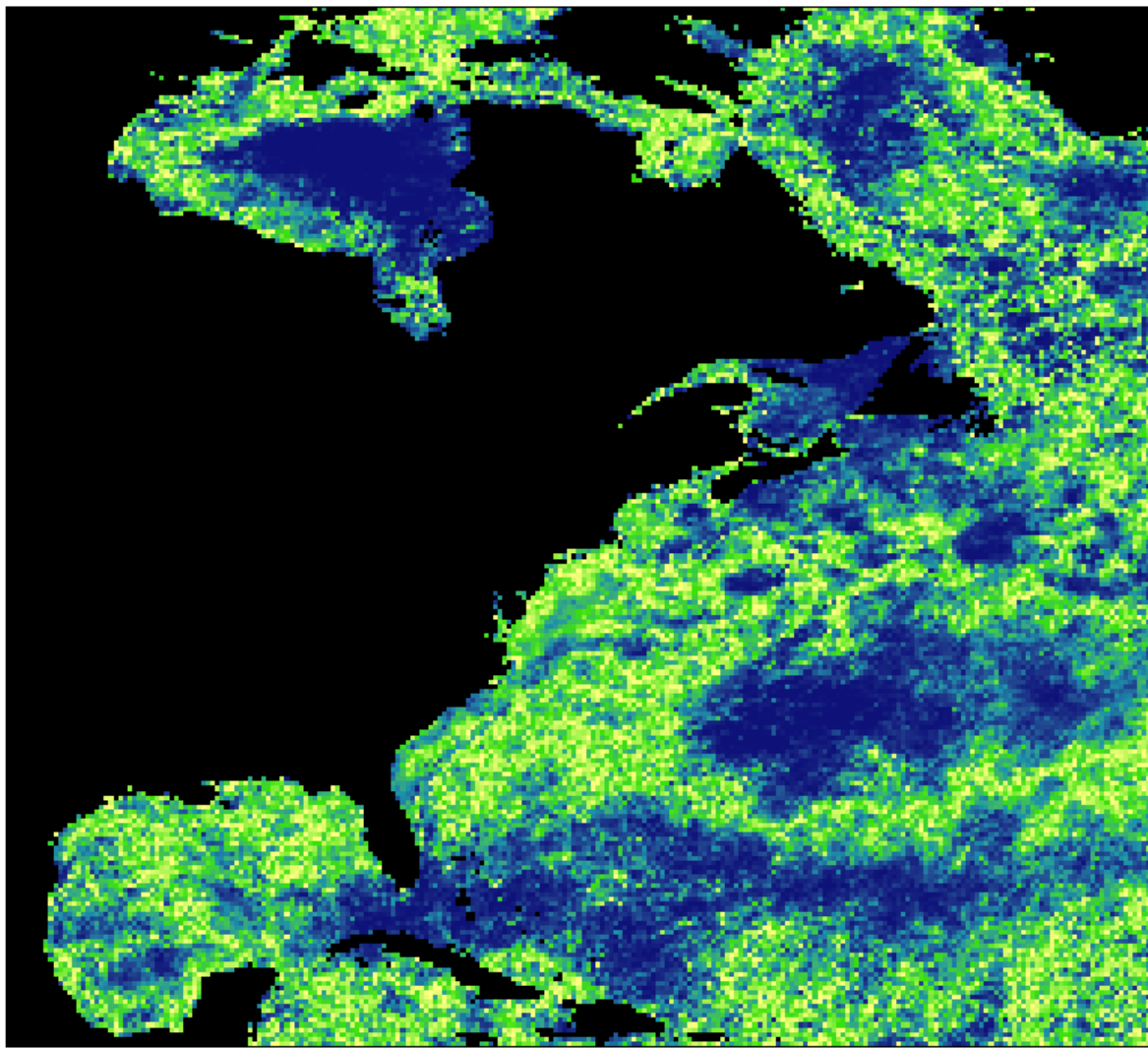


## July NAO v. July SST

R Squared

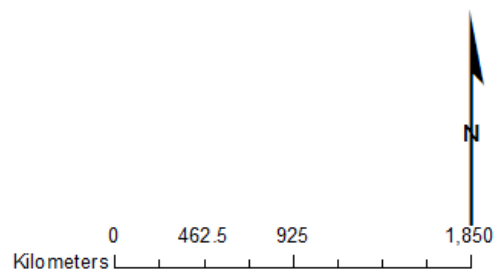
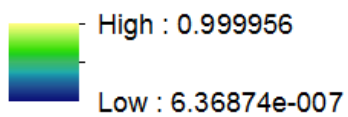


Ana Griefen 2014  
WGS 1984

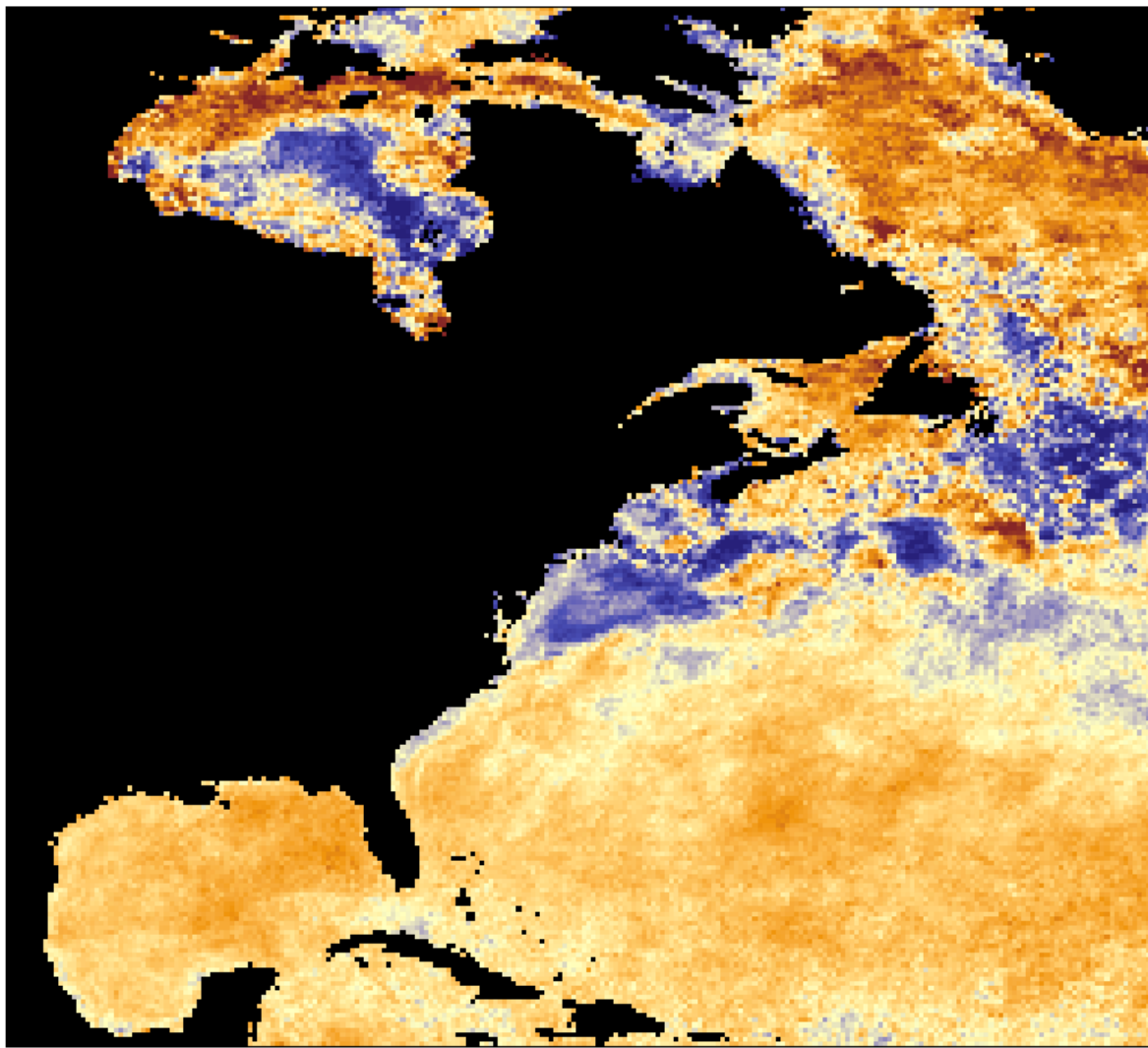


## July NAO v. July SST

P Value

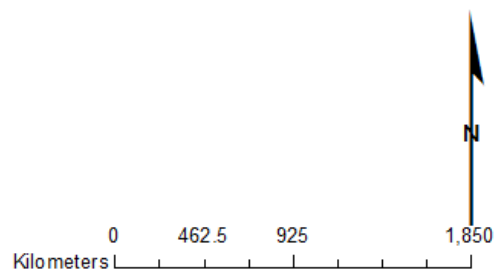
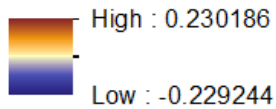


Ana Griefen 2014  
WGS 1984

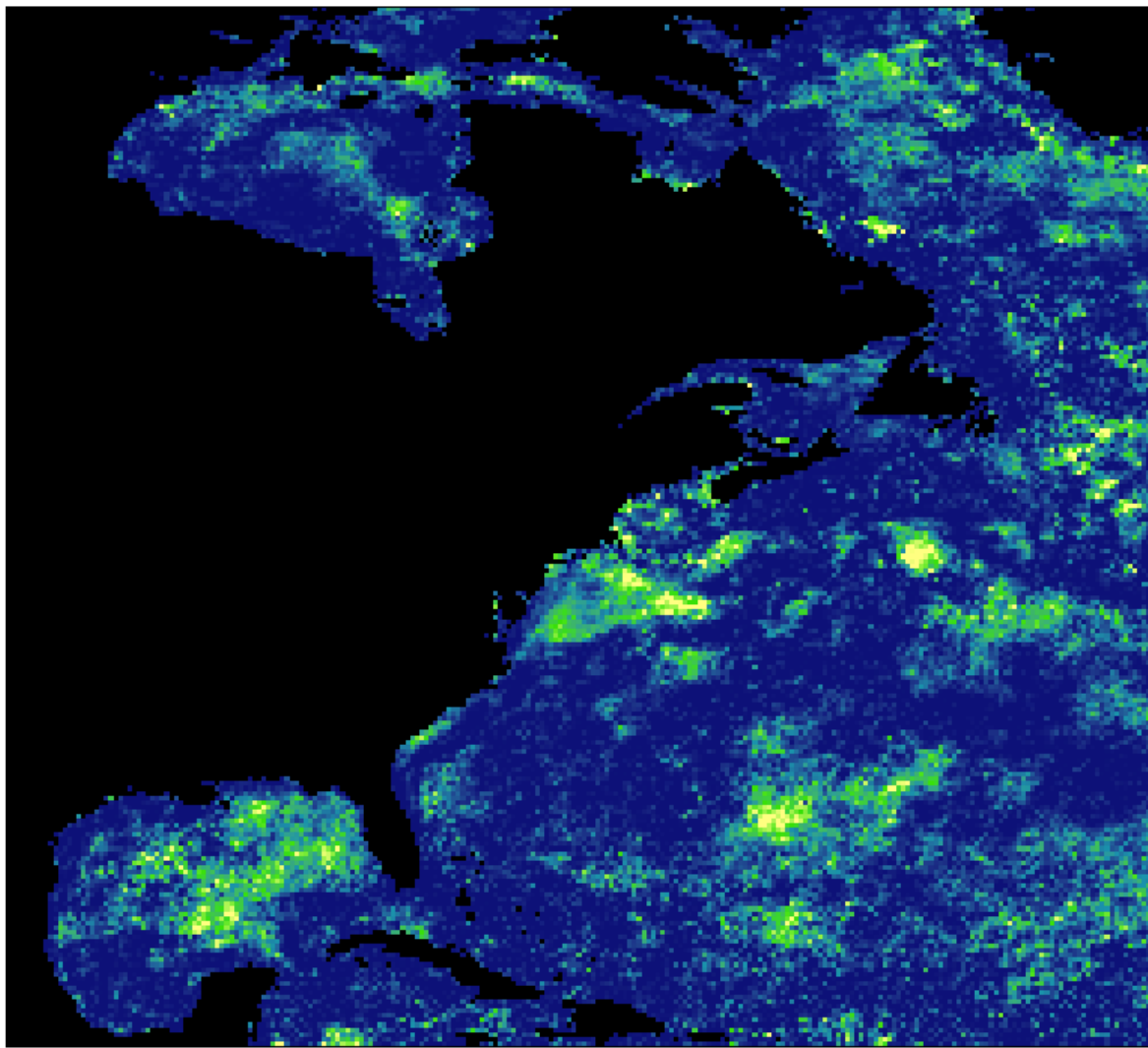


## Jan NAO v. July SST

Regression Coefficient

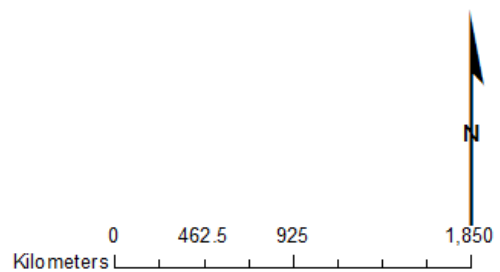
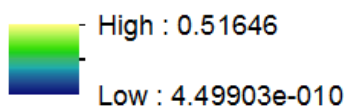


Ana Griefen 2014  
WGS 1984

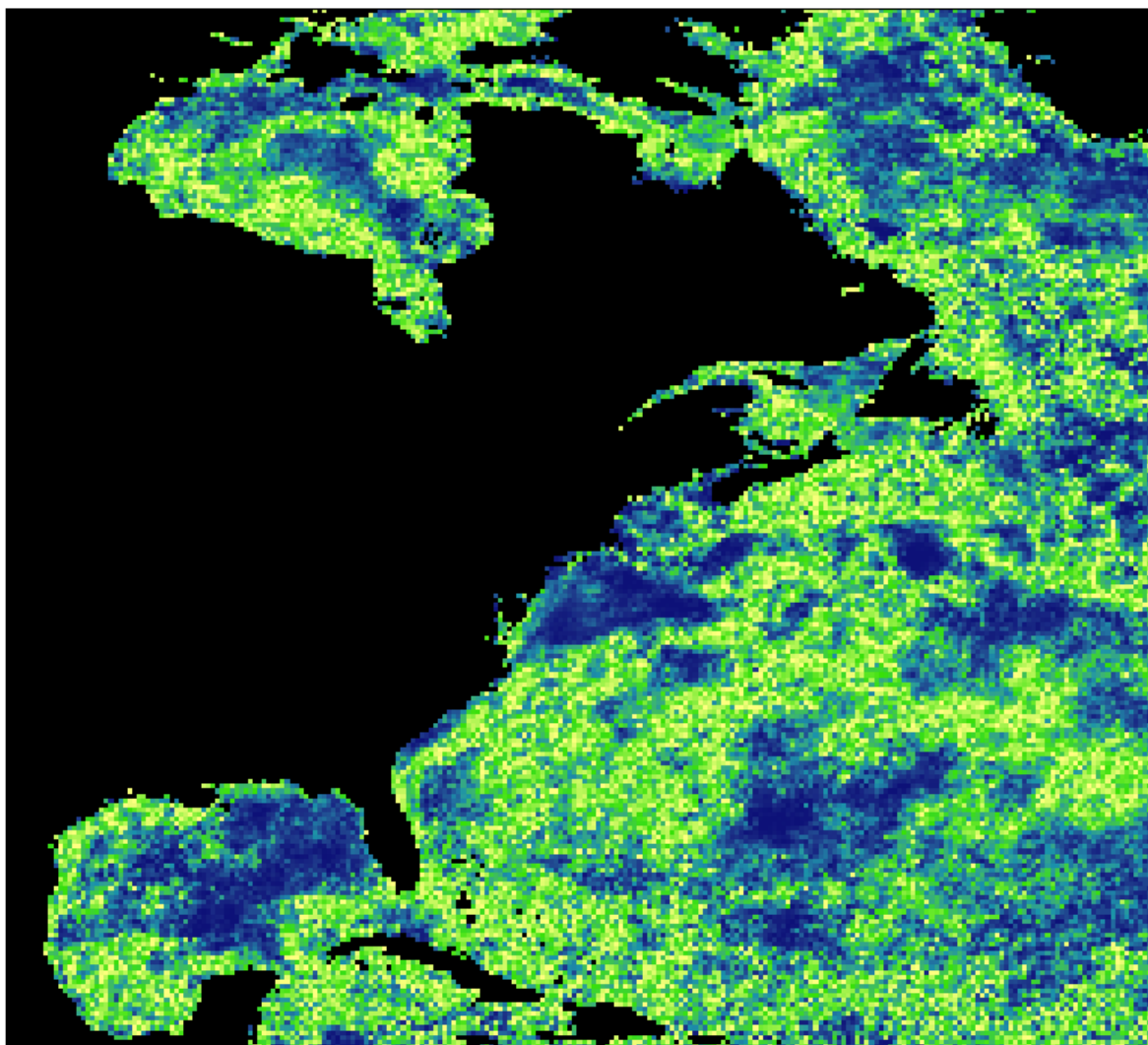


## Jan NAO v. July SST

R Squared

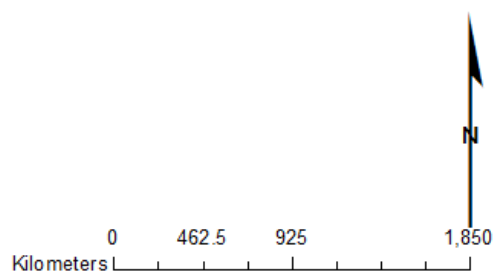
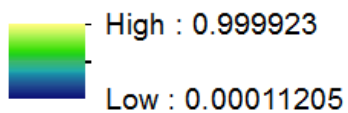


Ana Griefen 2014  
WGS 1984

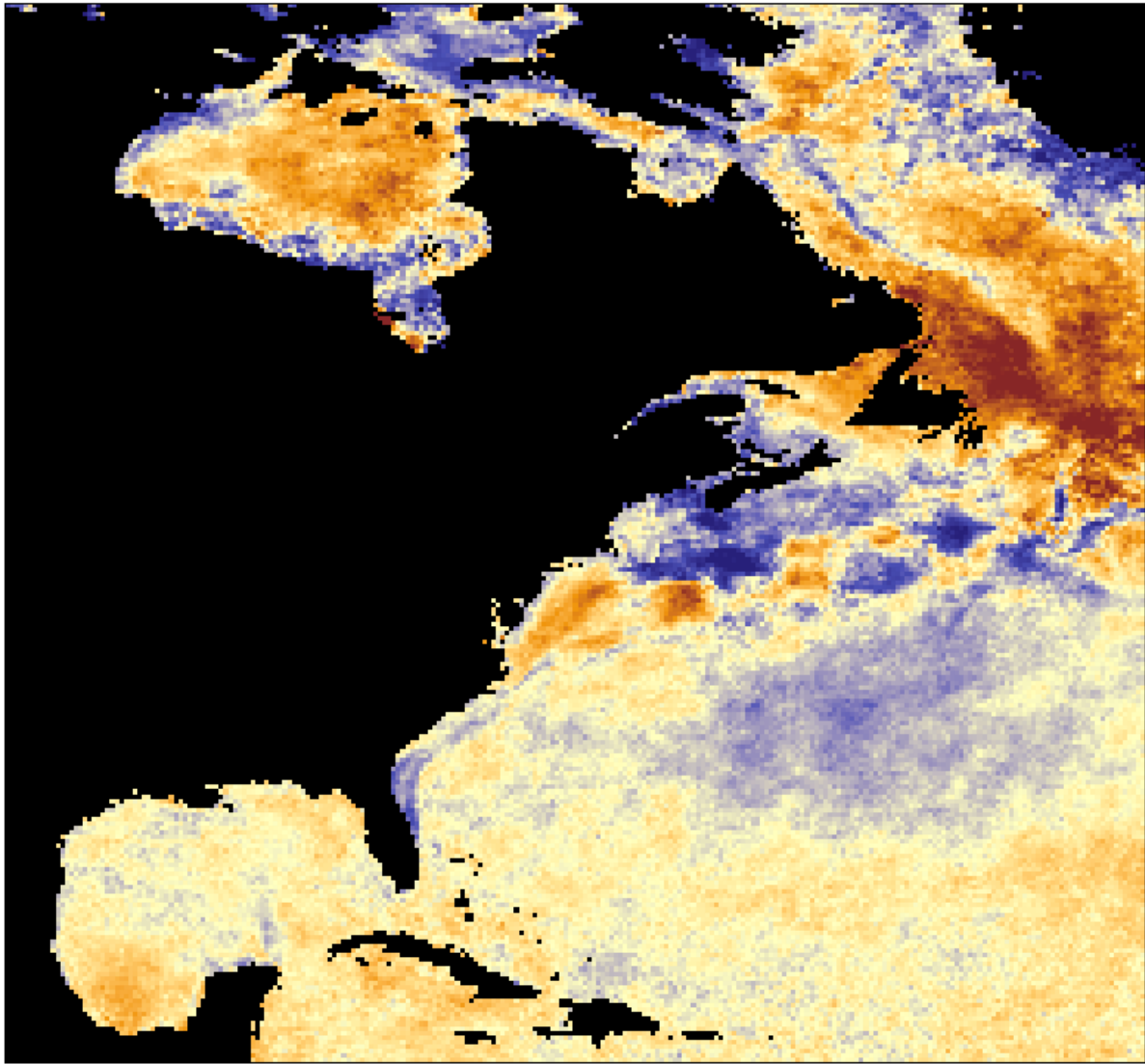


## Jan NAO v. July SST

P Value

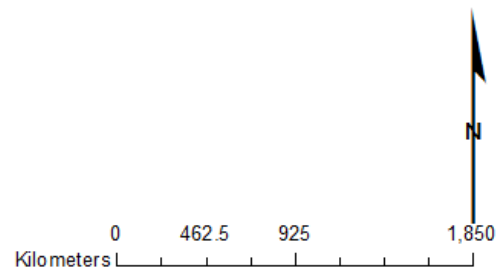
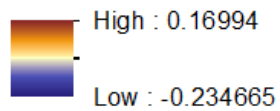


Ana Griefen 2014  
WGS 1984

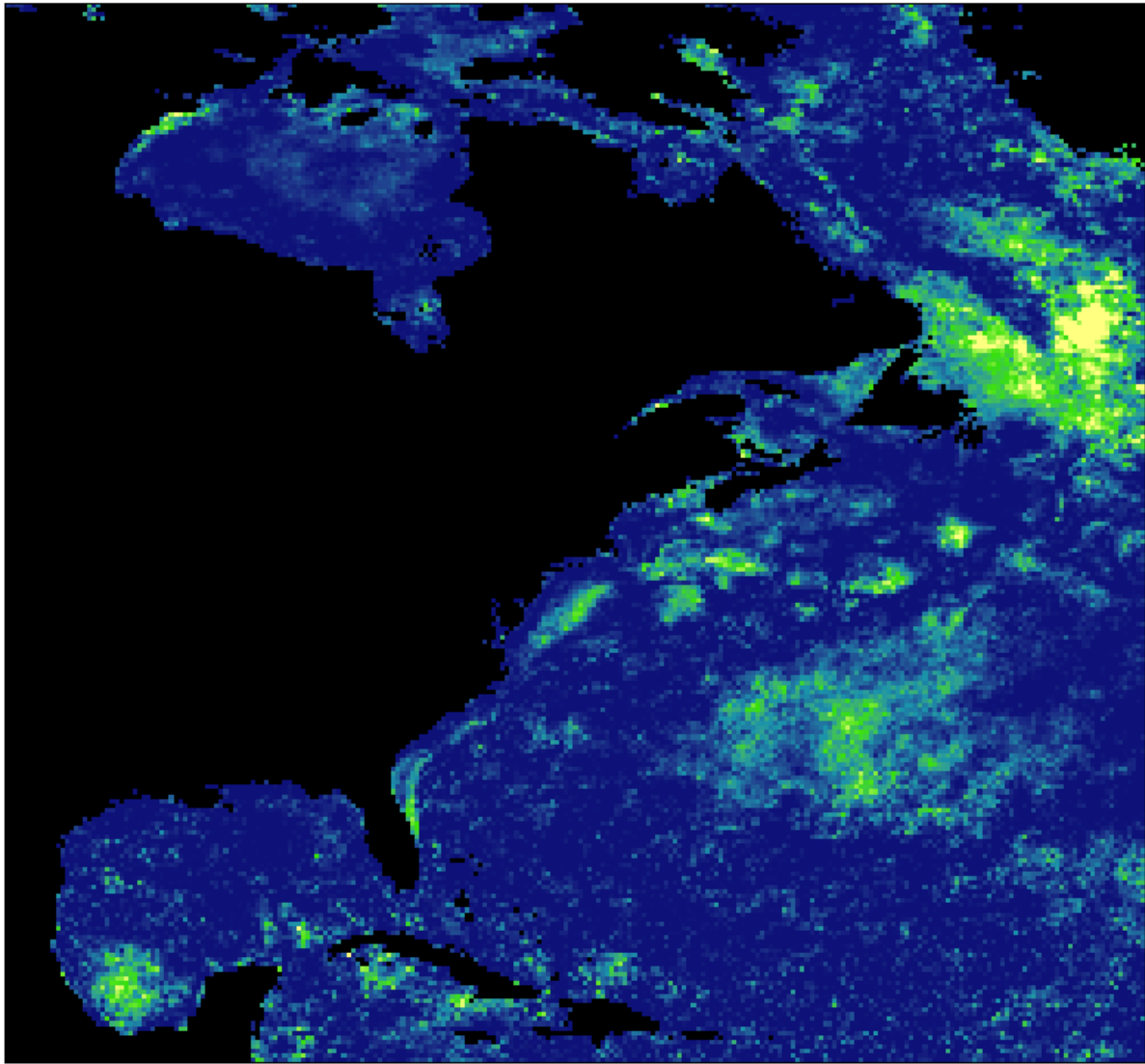


## August NAO v. August SST

Regression Coefficient

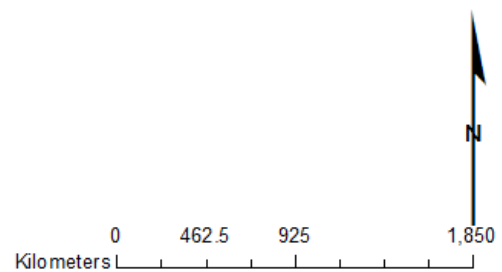
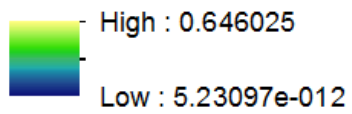


Ana Griefen 2014  
WGS 1984



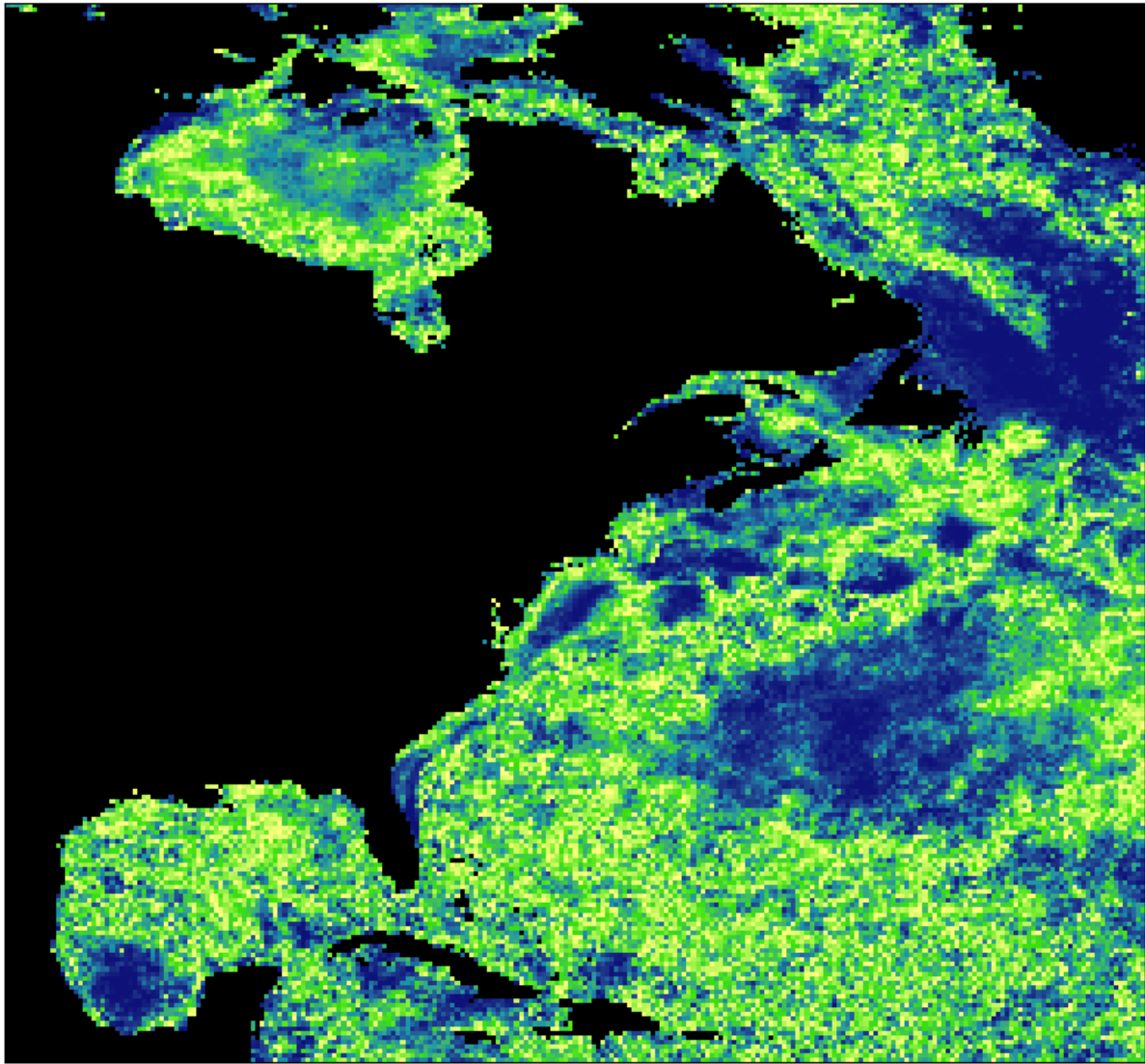
## August NAO v. August SST

R Squared



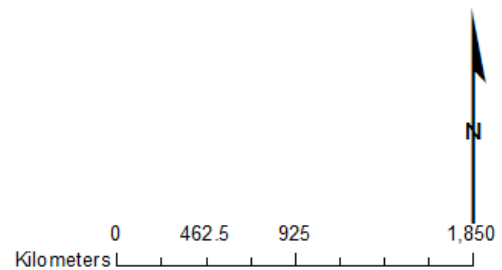
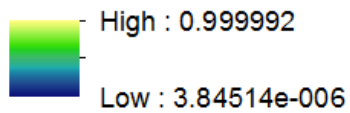
Ana Griefen 2014  
WGS 1984





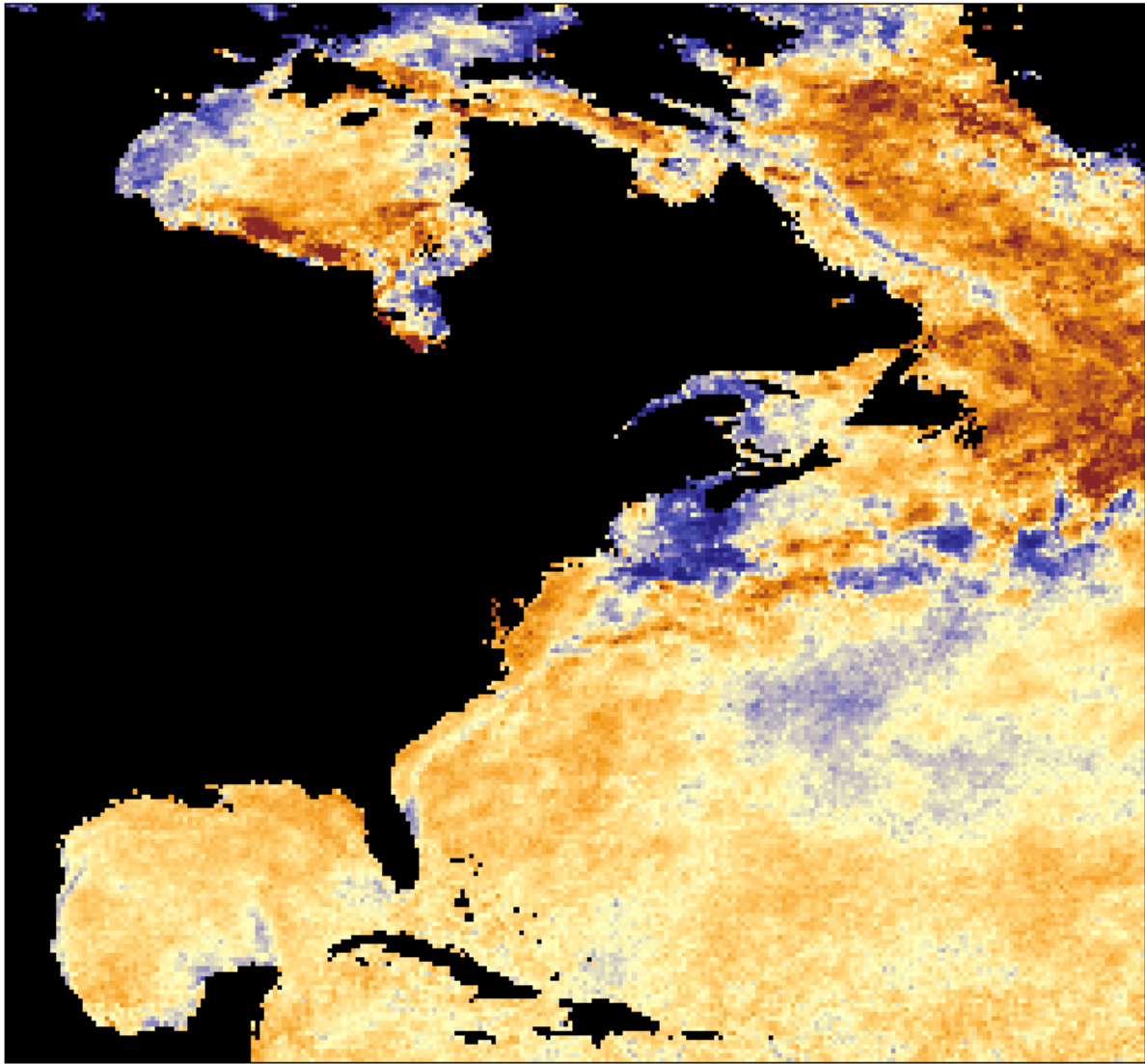
## August NAO v. August SST

P Value



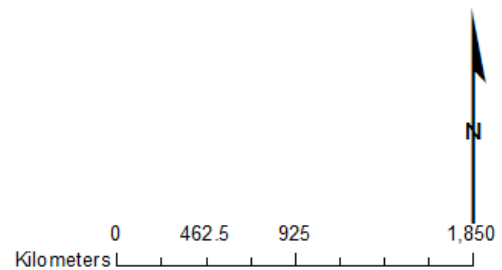
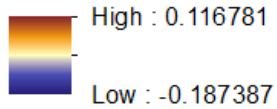
Ana Griefen 2014  
WGS 1984



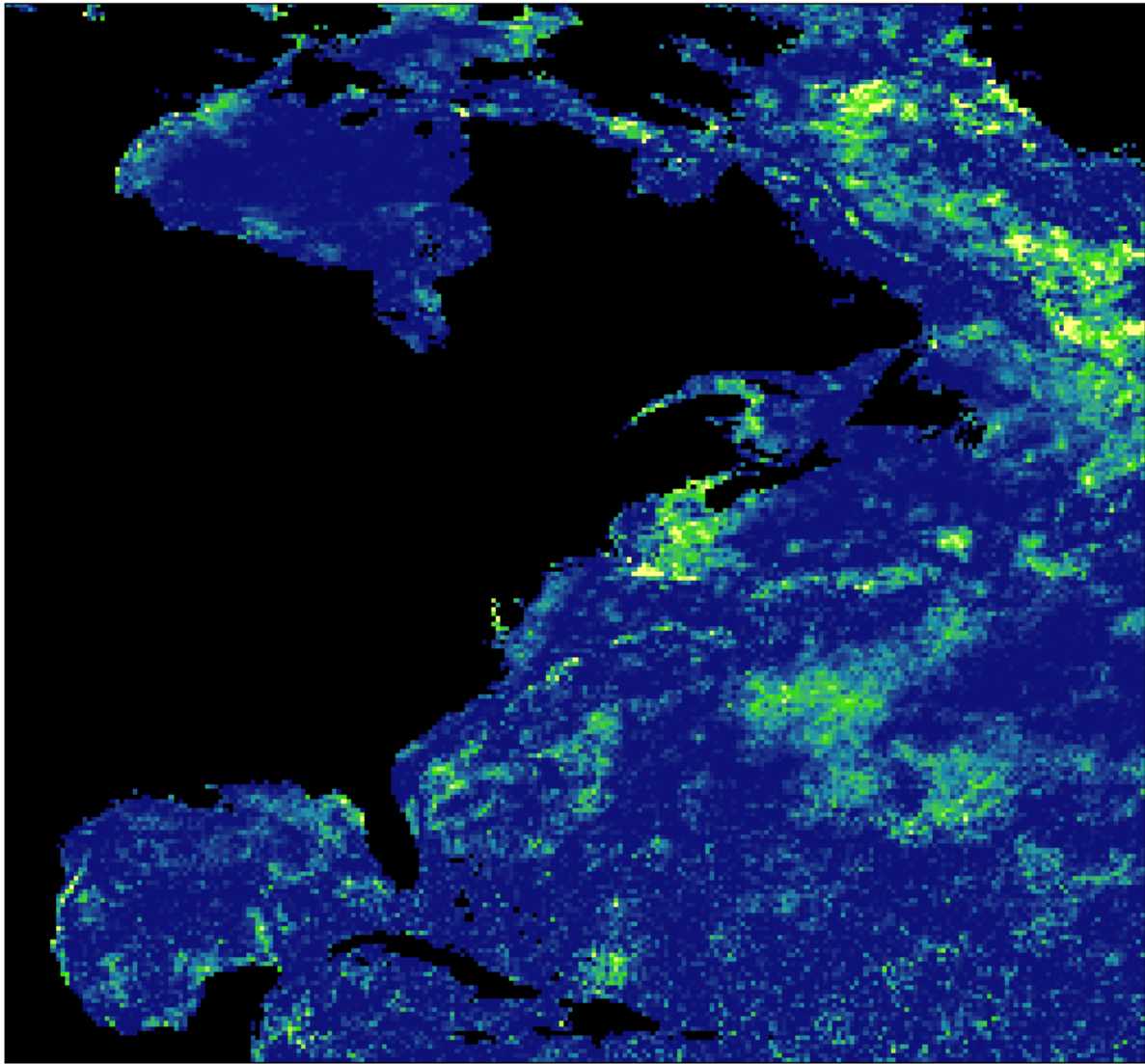


## February NAO v. August SST

Regression Coefficient

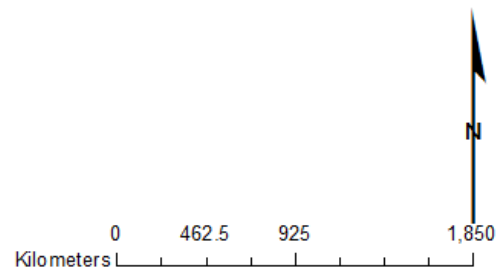
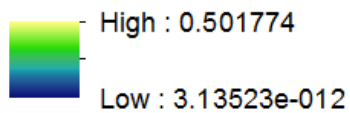


Ana Griefen 2014  
WGS 1984

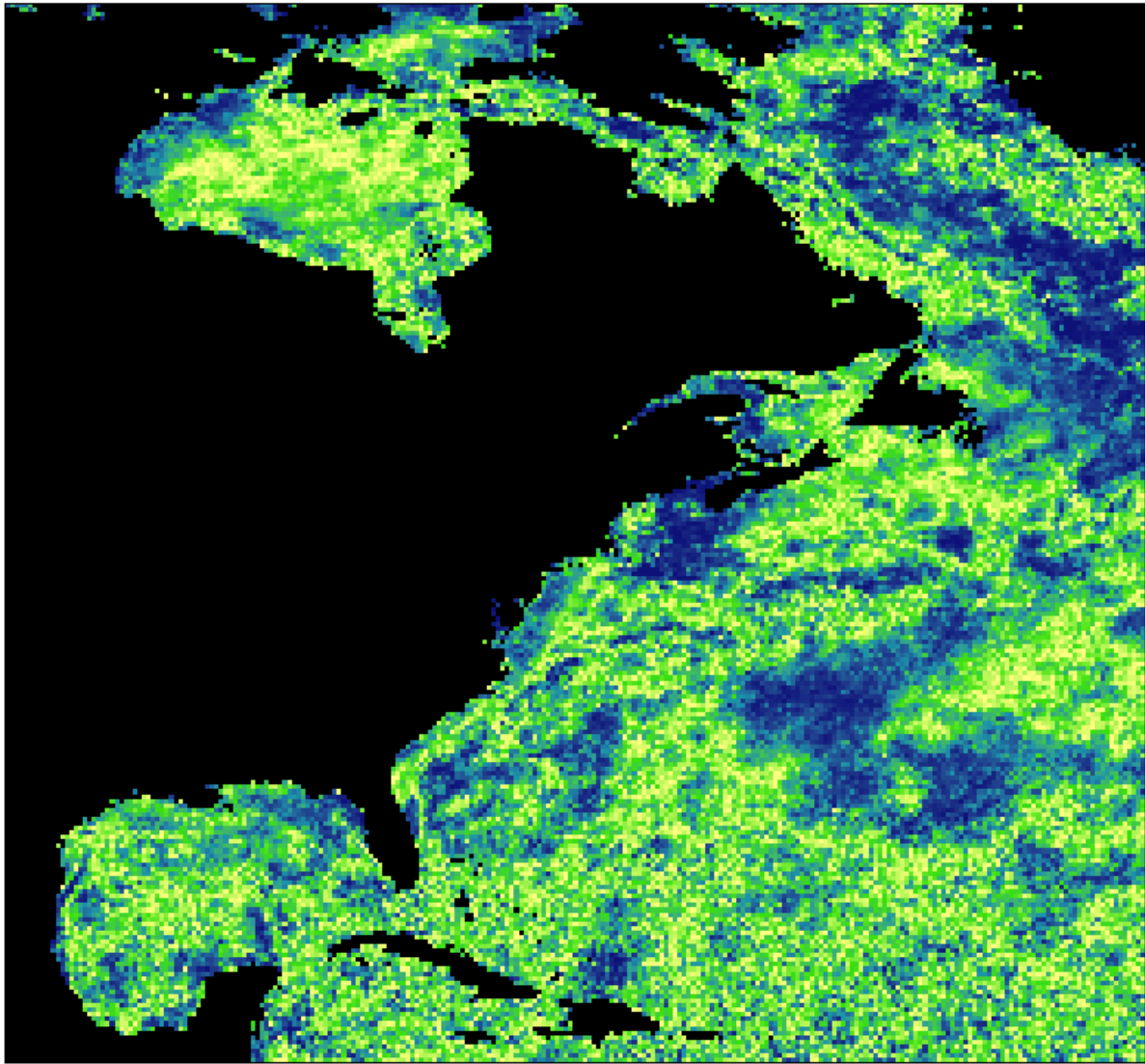


## February NAO v. August SST

R Squared

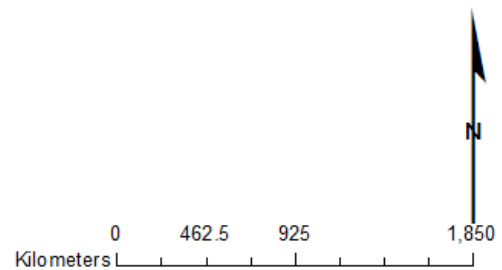
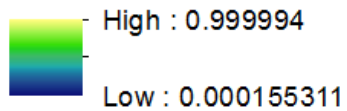


Ana Griefen 2014  
WGS 1984

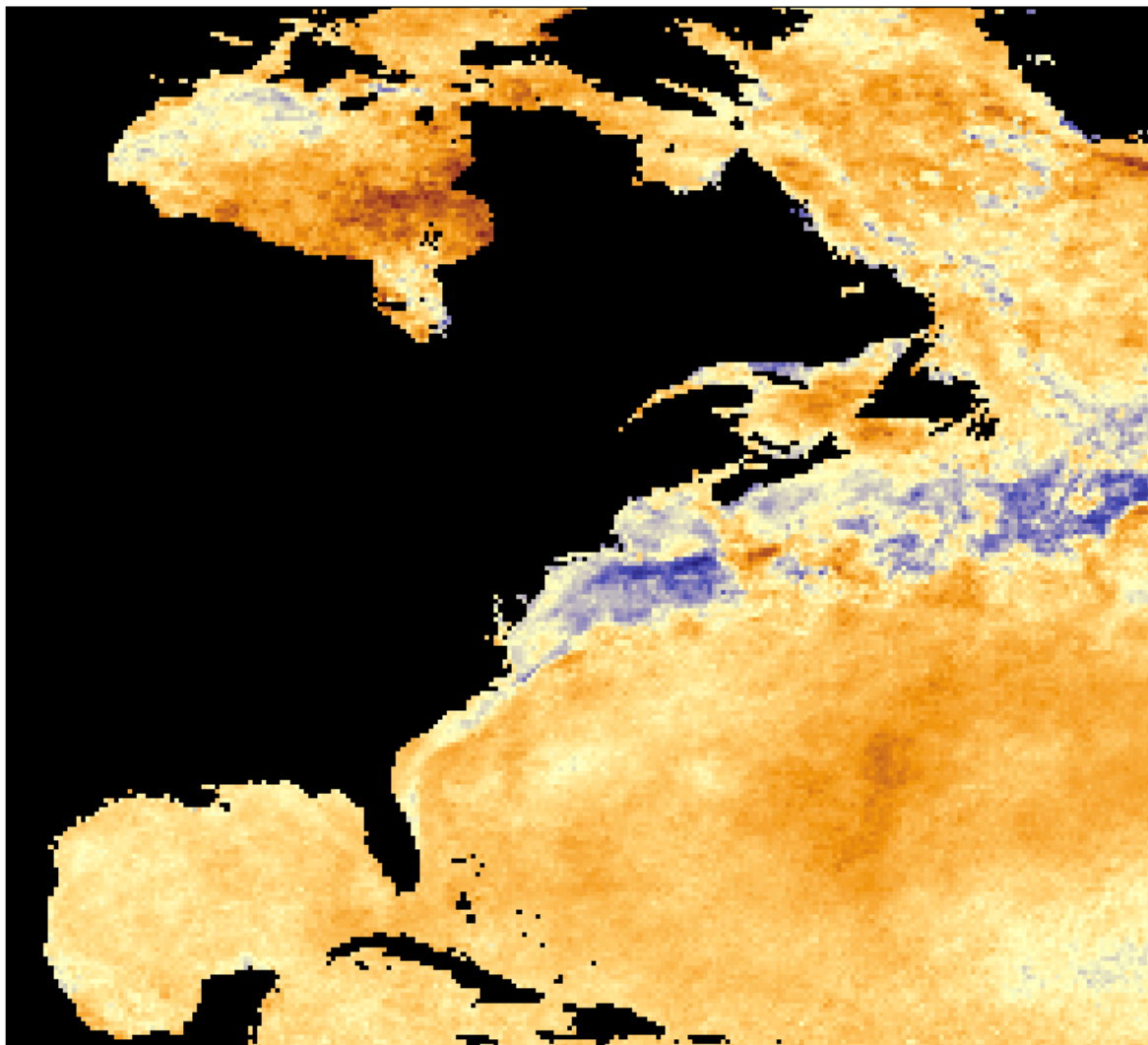


## February NAO v. August SST

P Value

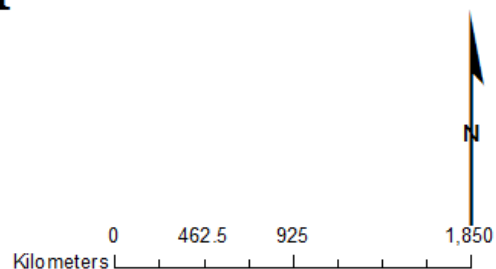
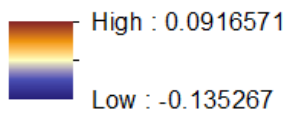


Ana Griefen 2014  
WGS 1984

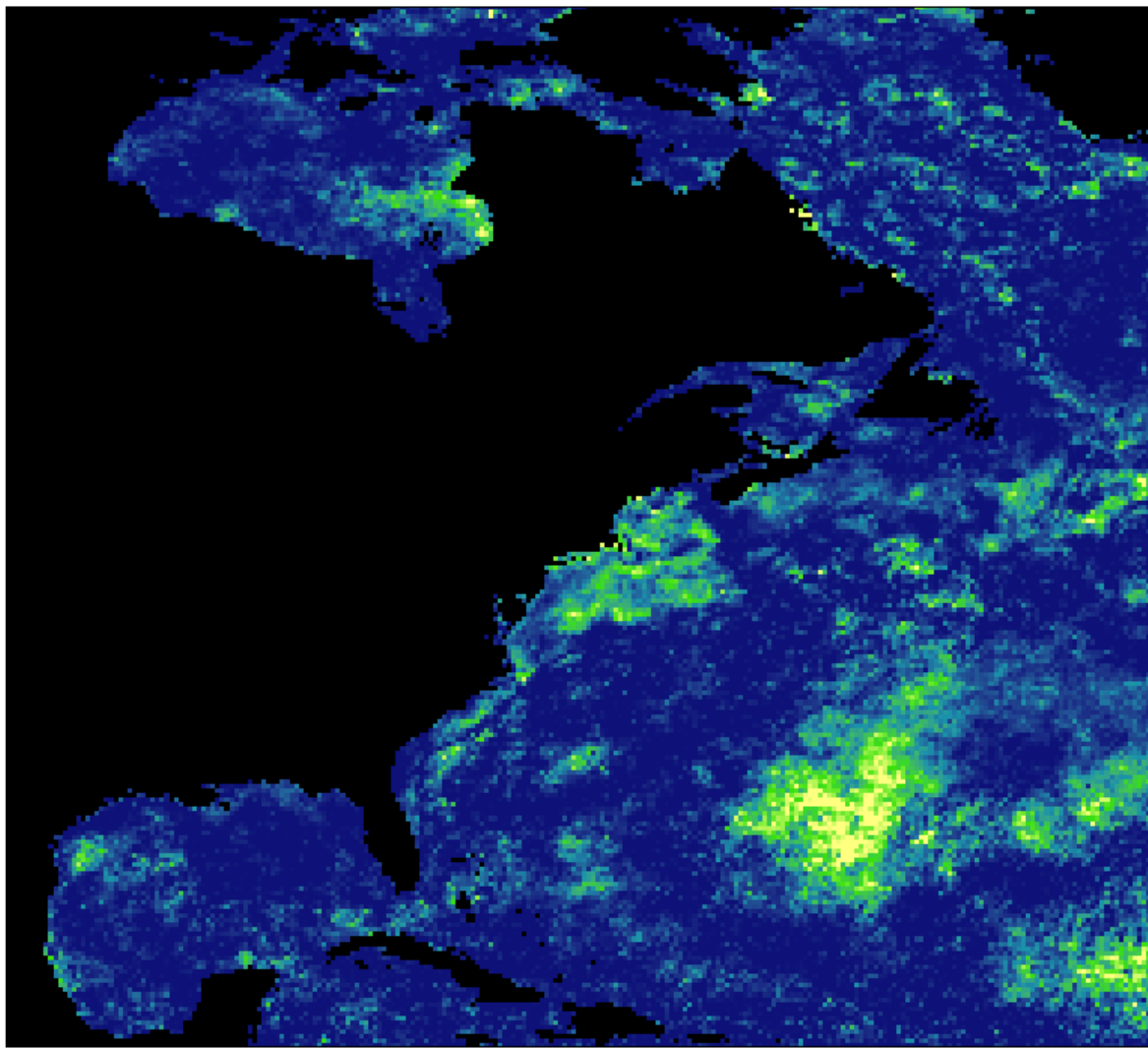


## September NAO v. September SST

Regression Coefficient

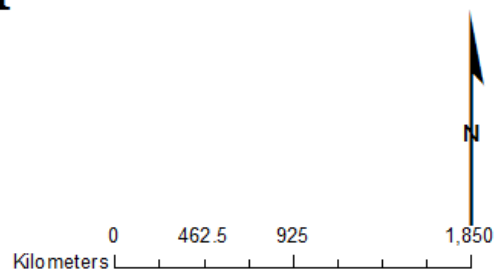
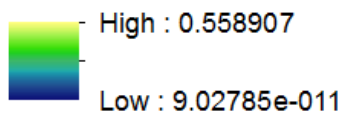


Ana Griefen 2014  
WGS 1984

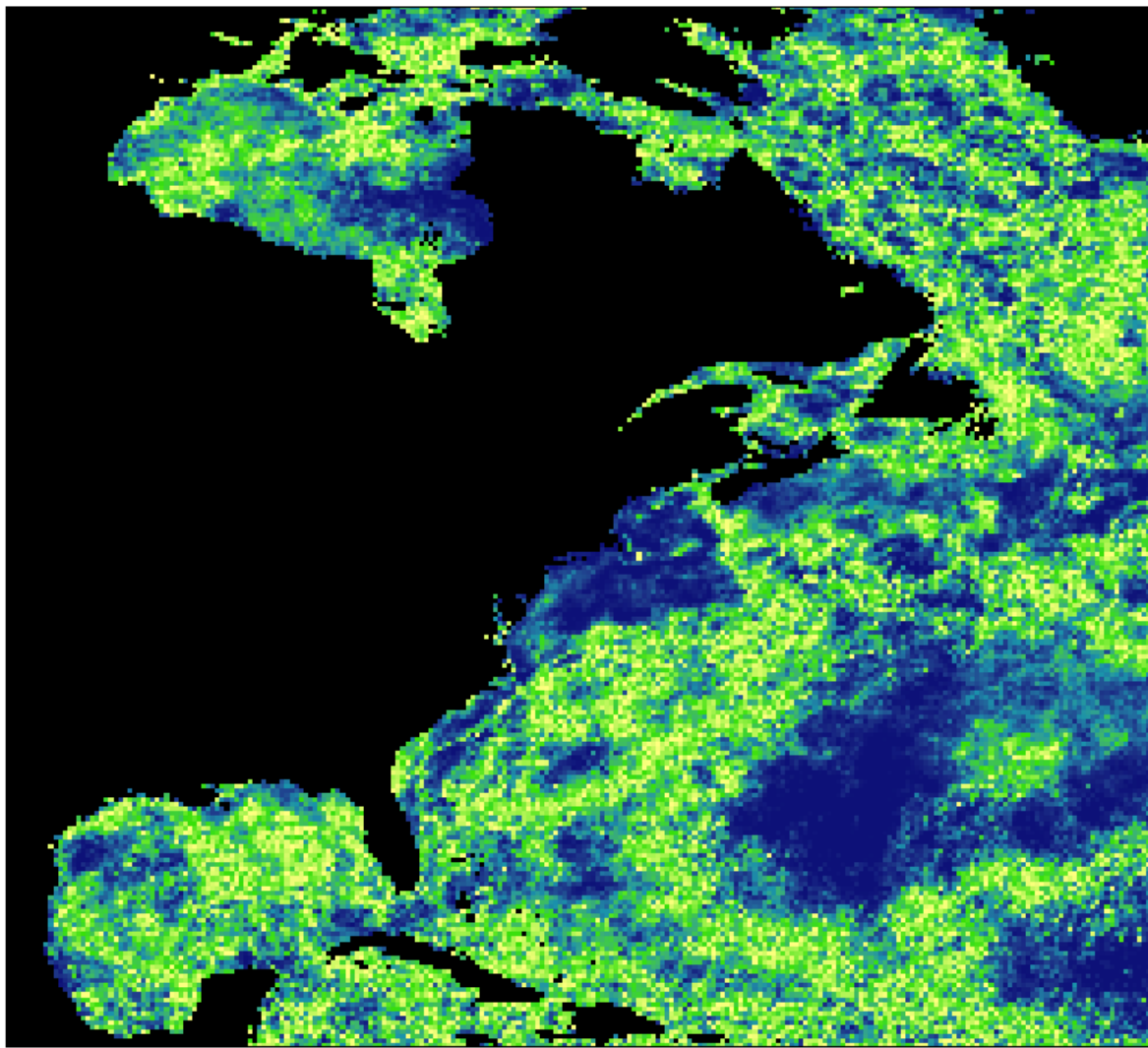


## September NAO v. September SST

R Squared

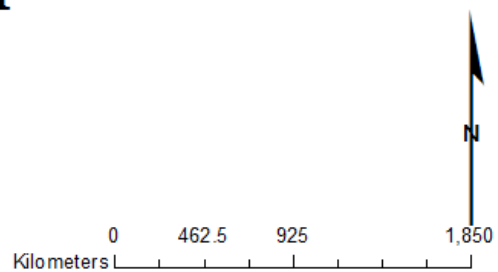
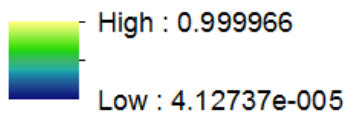


Ana Griefen 2014  
WGS 1984

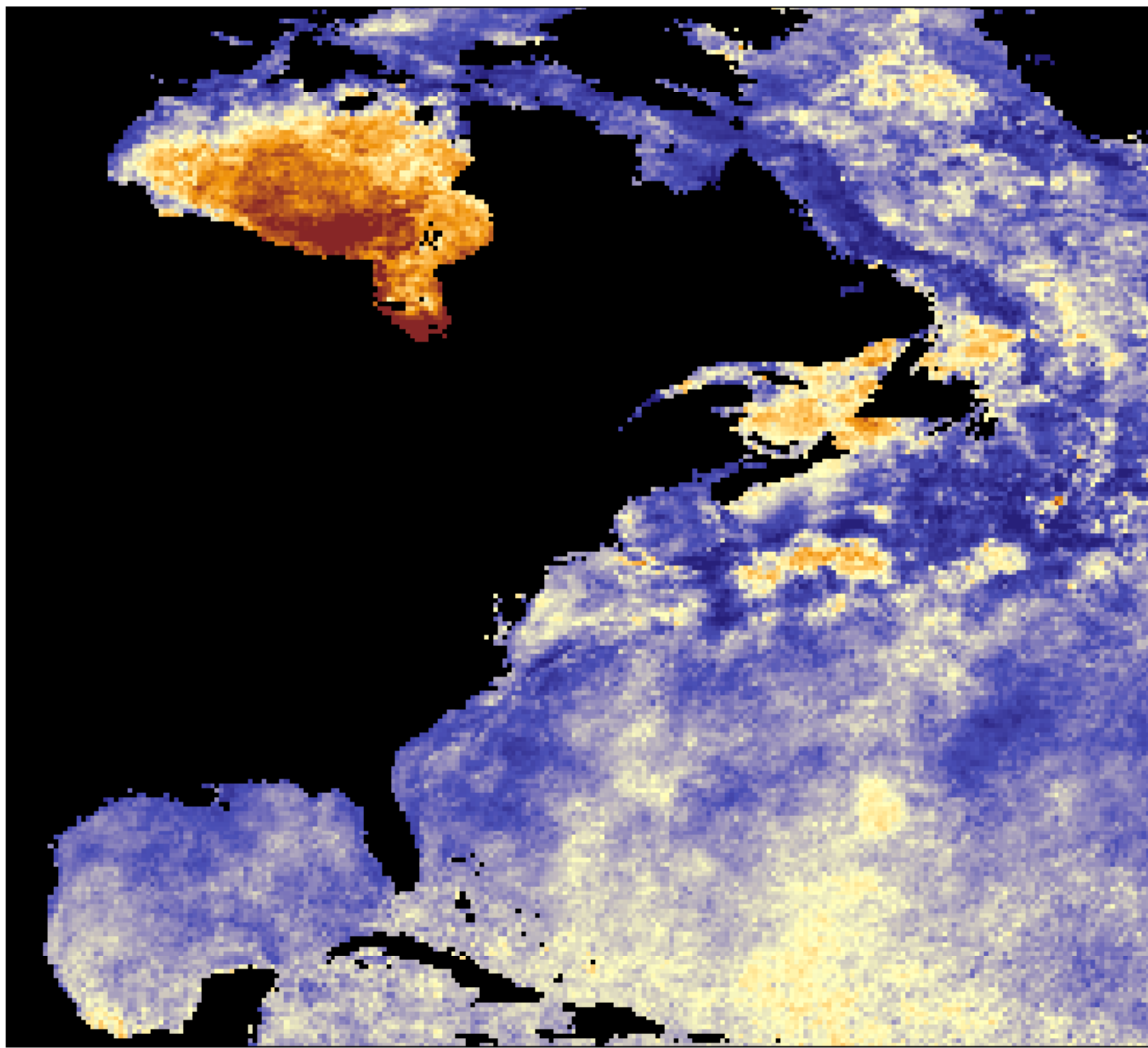


## September NAO v. September SST

P Value

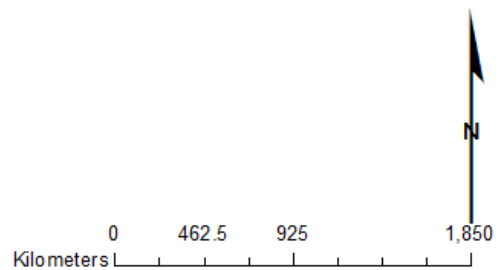
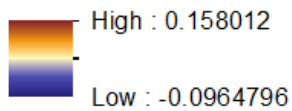


Ana Griefen 2014  
WGS 1984



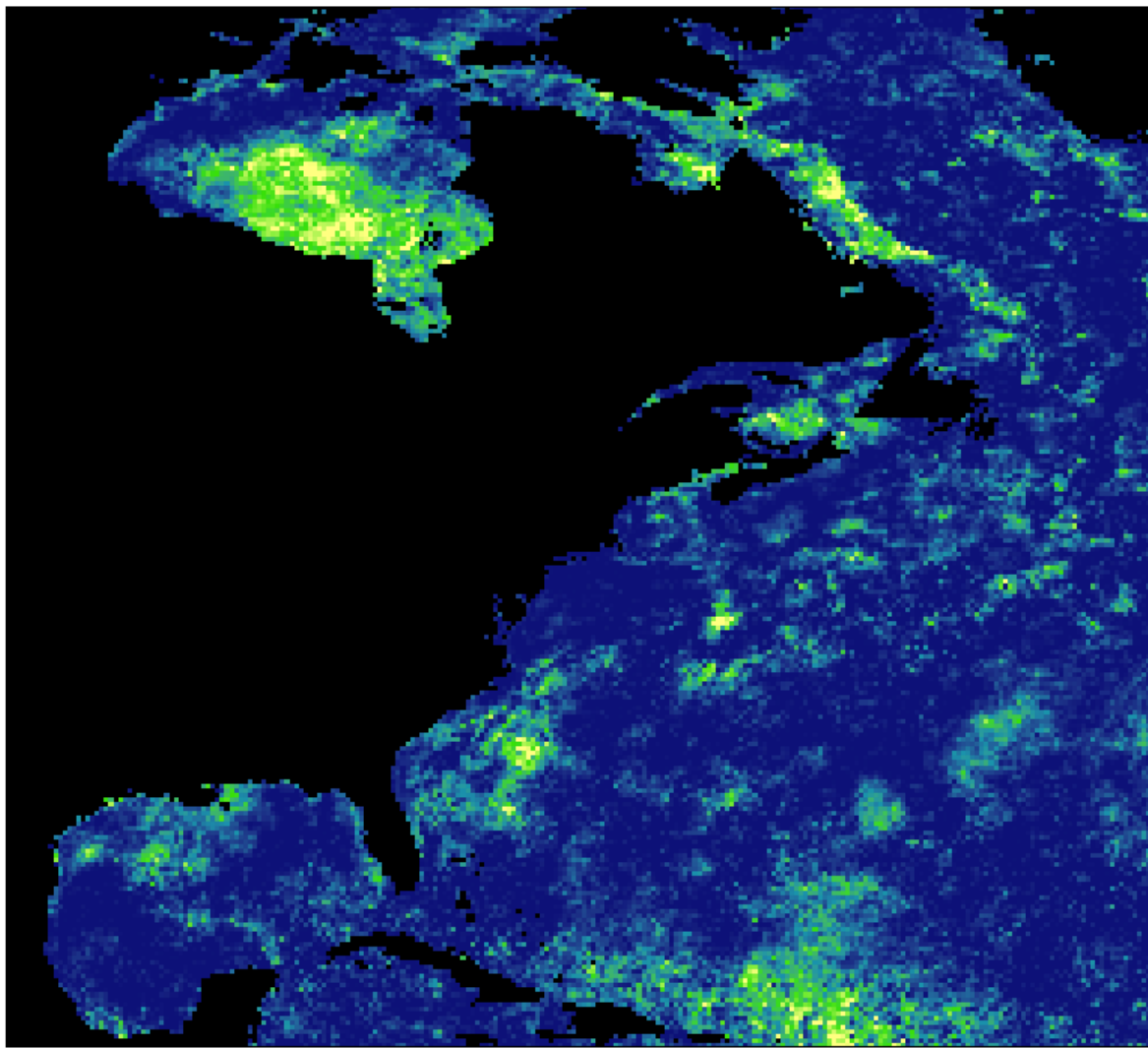
## March NAO v. September SST

Regression Coefficient



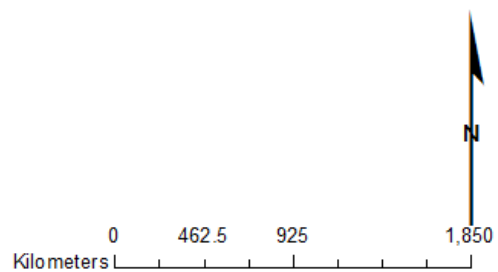
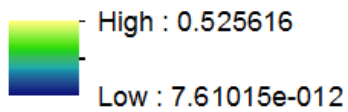
Ana Griefen 2014  
WGS 1984





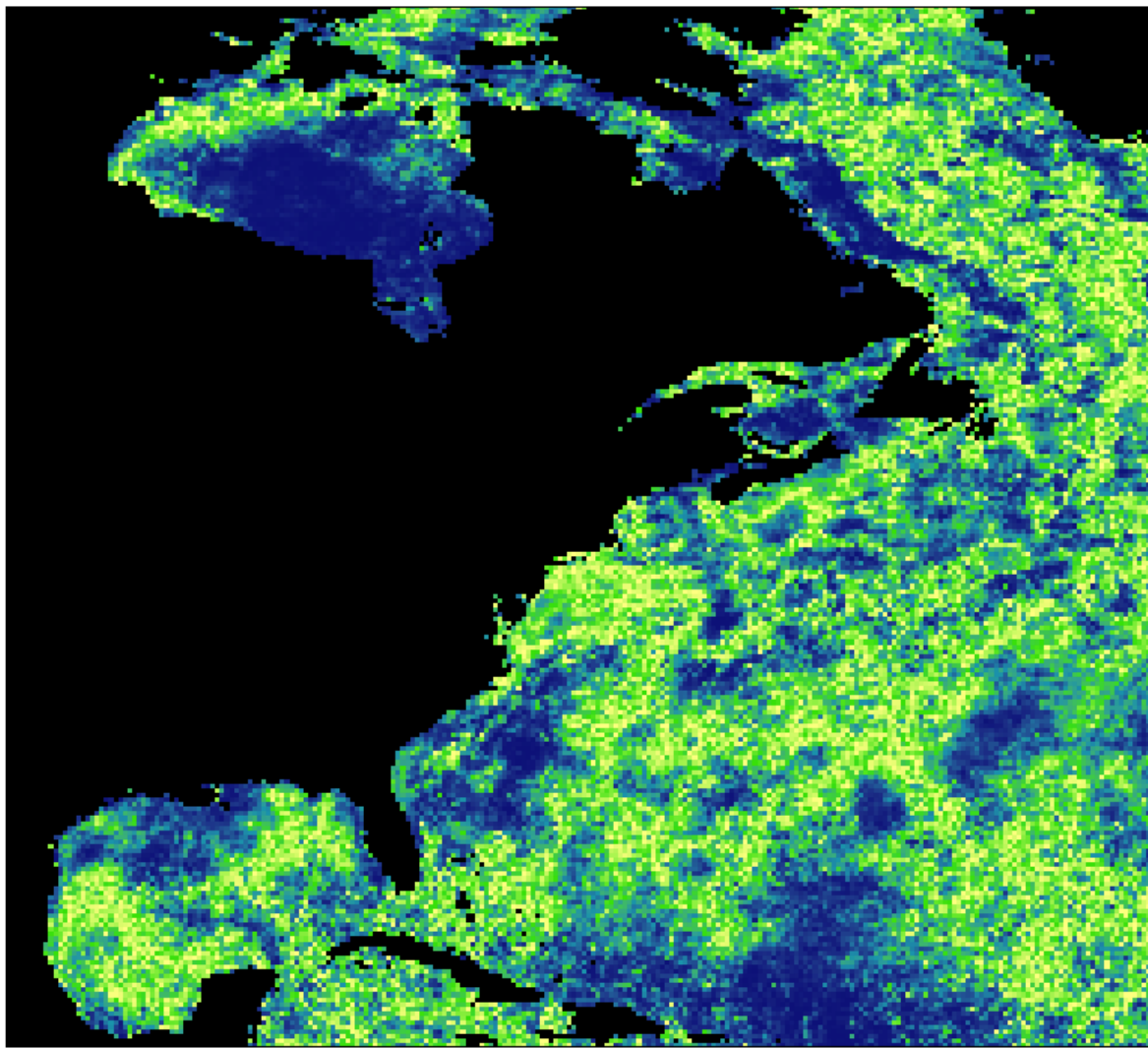
## March NAO v. September SST

R Squared



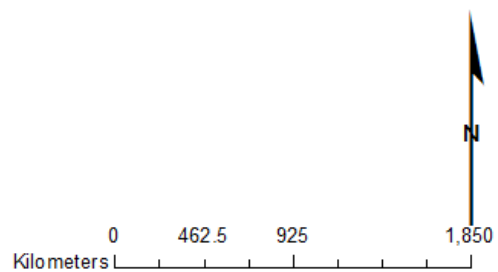
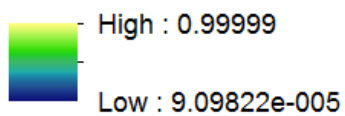
Ana Griefen 2014  
WGS 1984



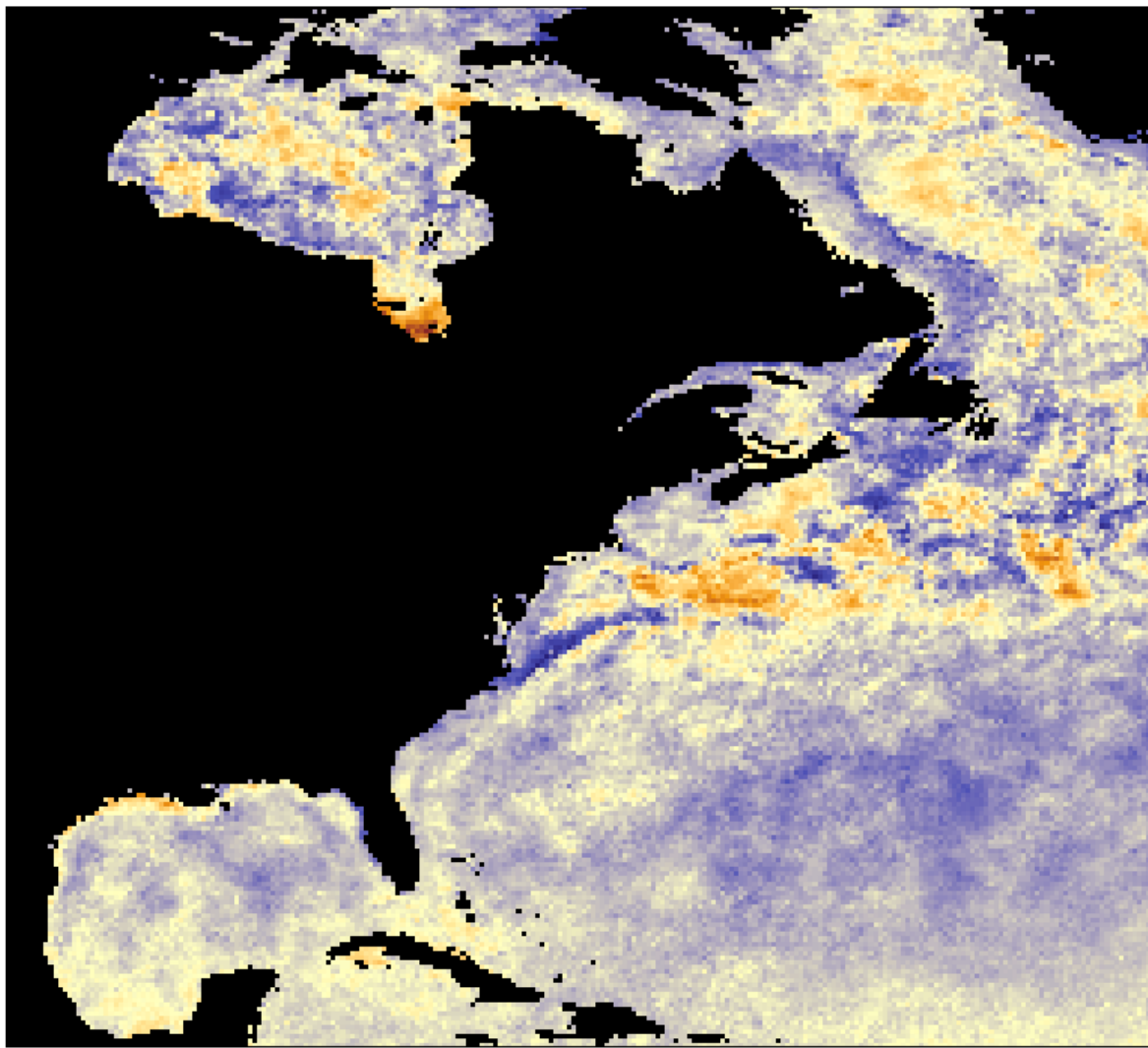


## March NAO v. September SST

P Value

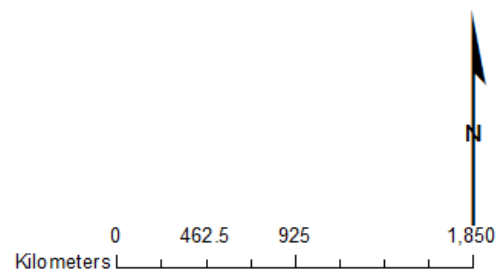
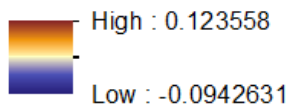


Ana Griefen 2014  
WGS 1984

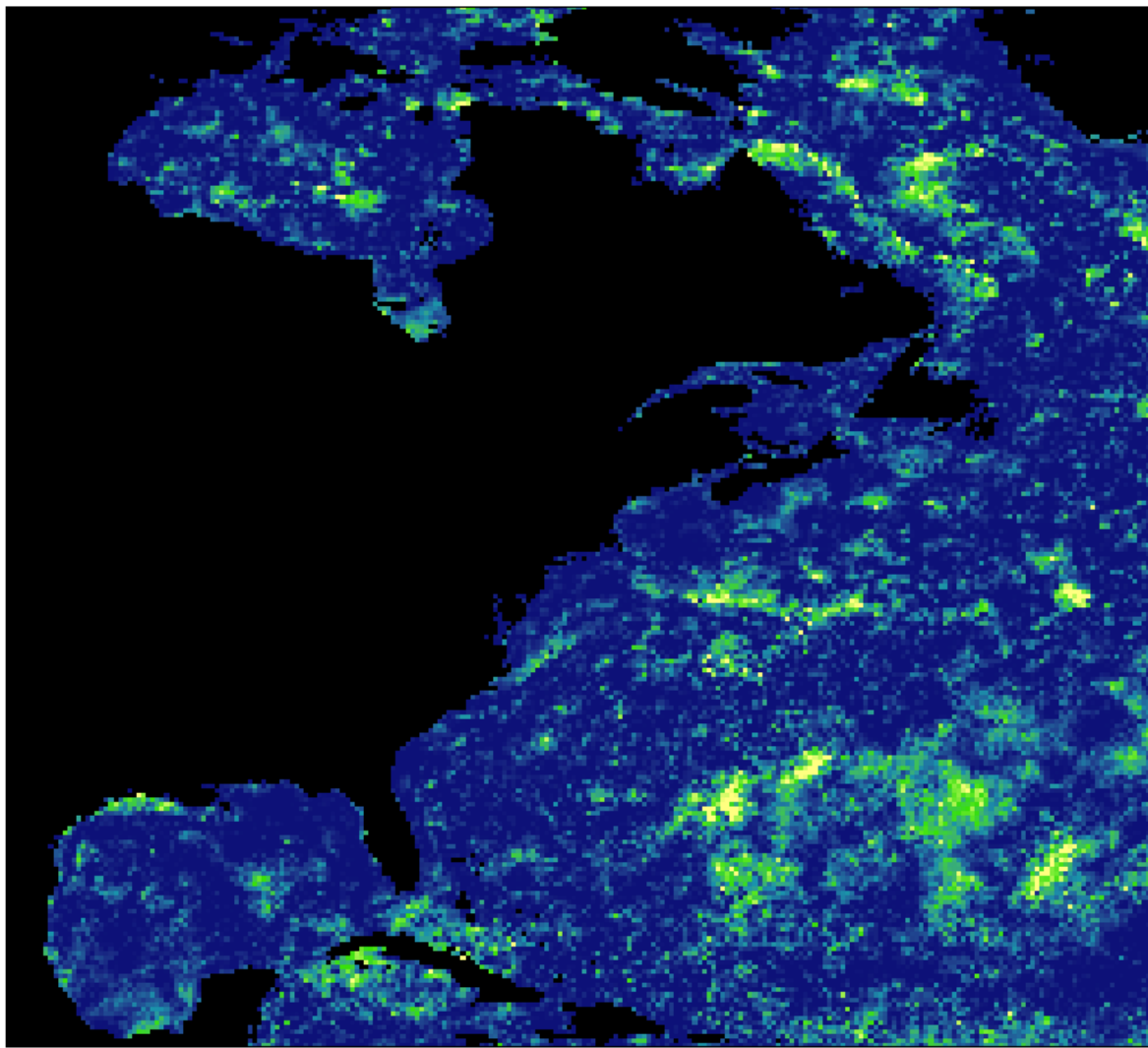


## October NAO v. October SST

Regression Coefficient

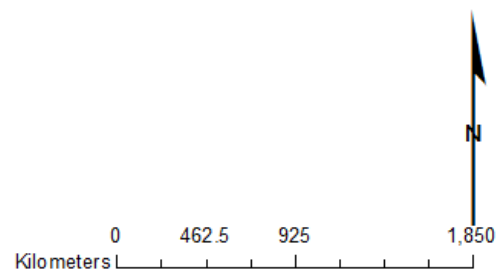
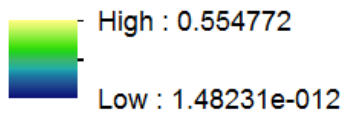


Ana Griefen 2014  
WGS 1984

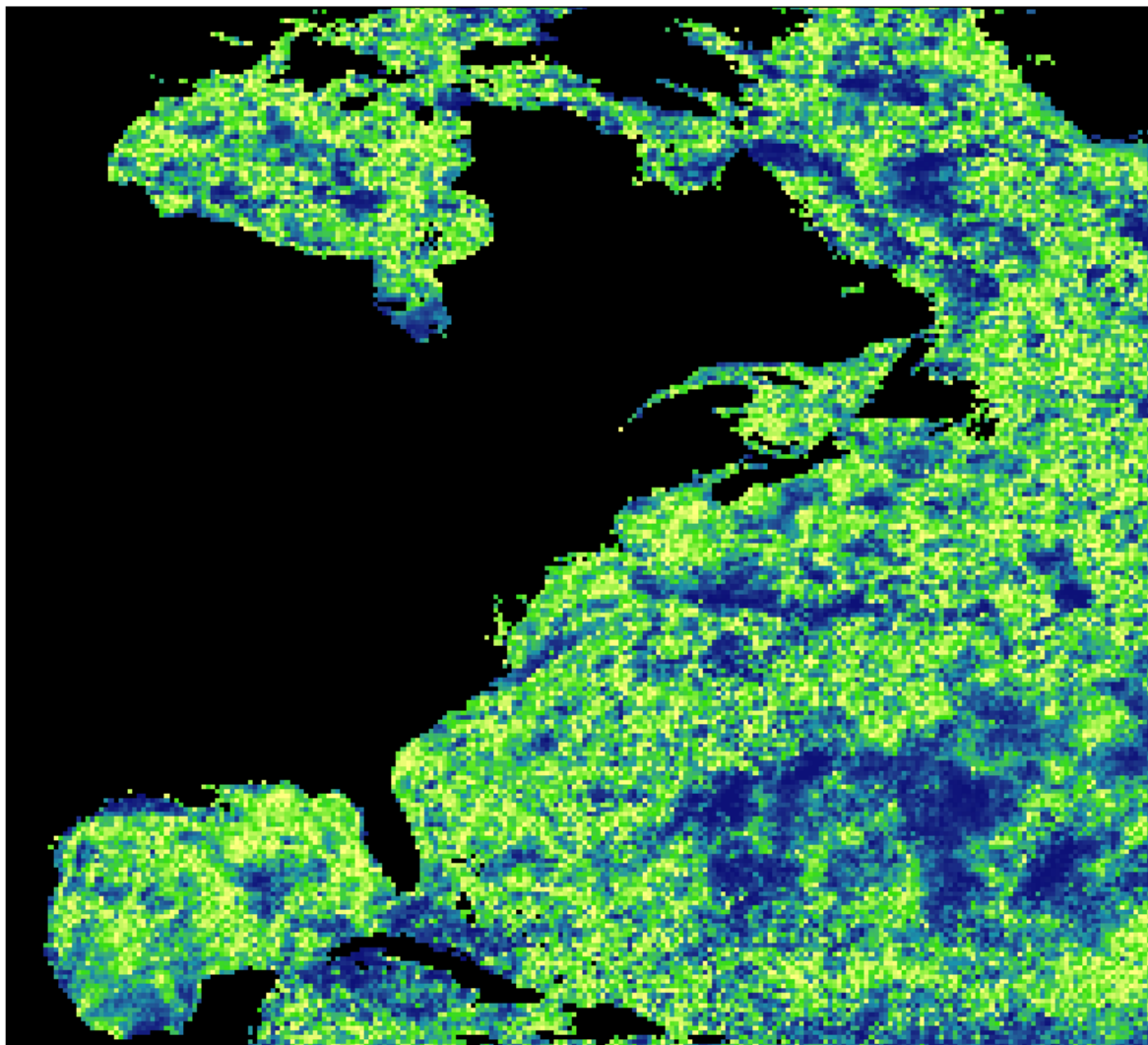


## October NAO v. October SST

R Squared

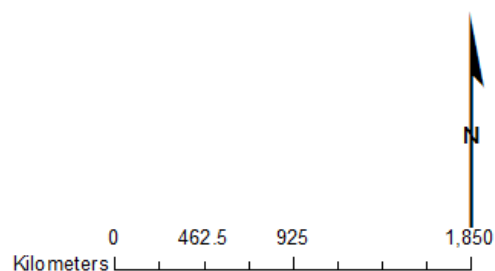
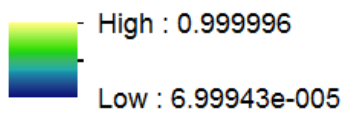


Ana Griefen 2014  
WGS 1984

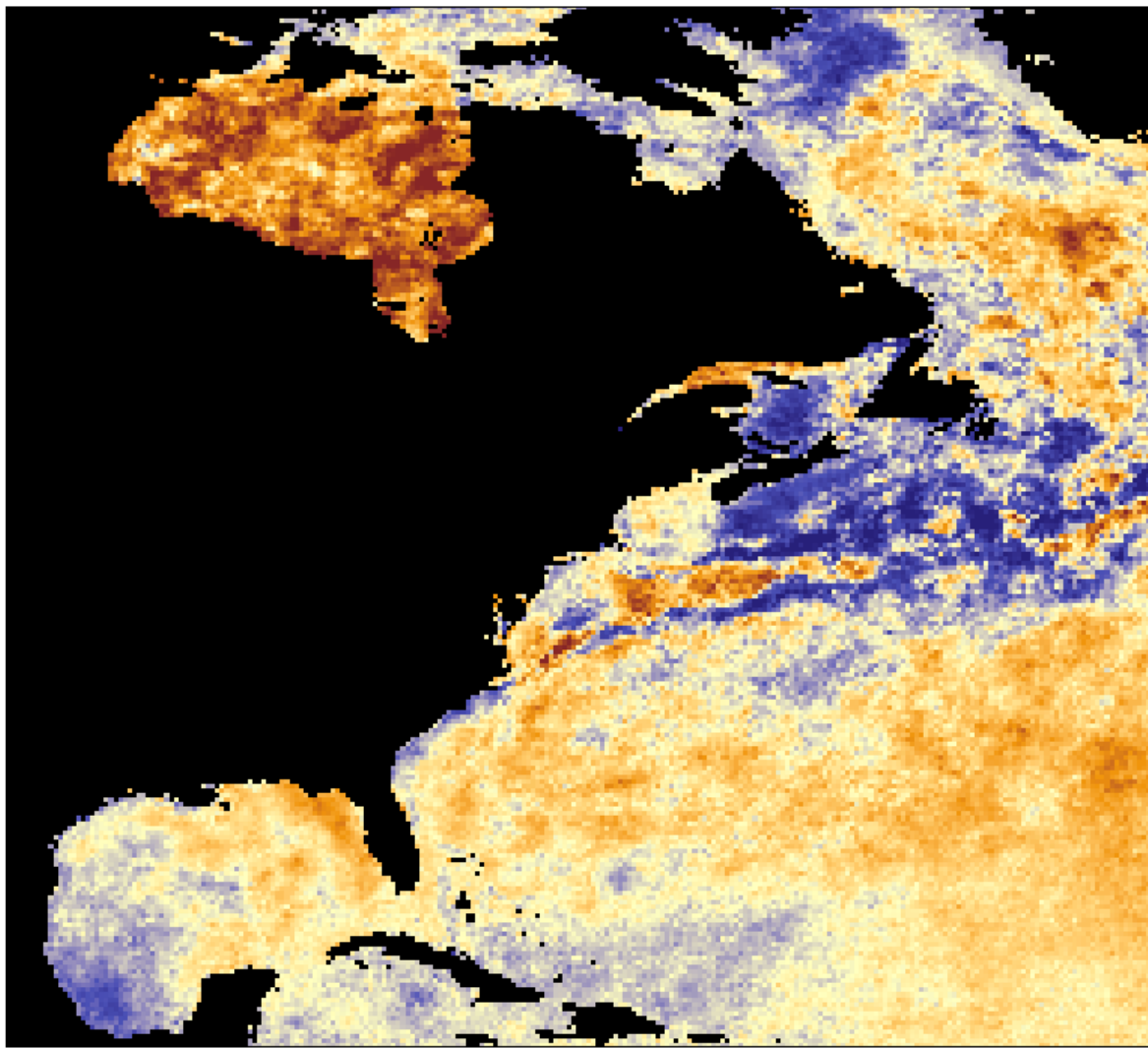


## October NAO v. October SST

P Value

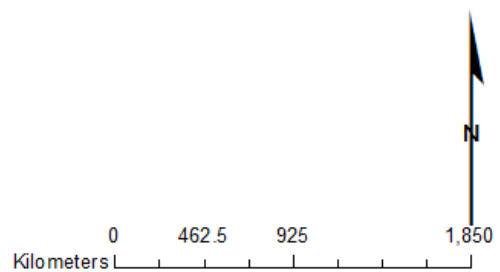
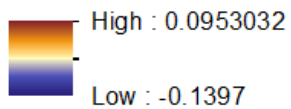


Ana Griefen 2014  
WGS 1984

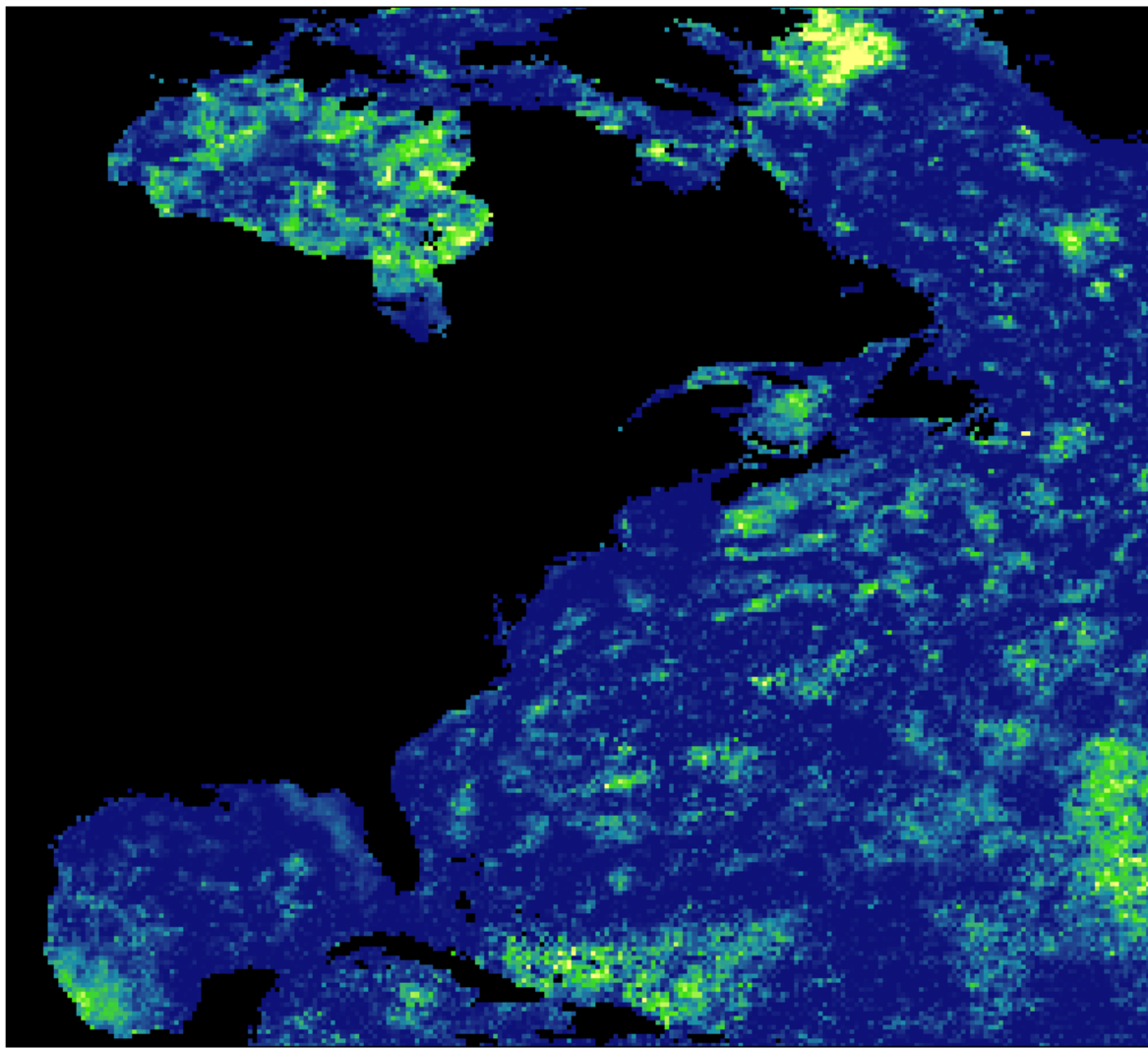


## April NAO v. October SST

Regression Coefficient

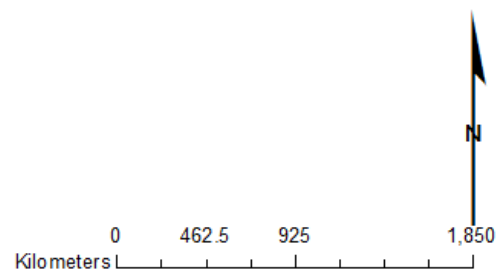
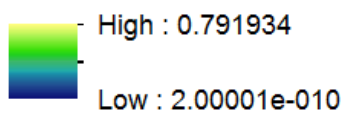


Ana Griefen 2014  
WGS 1984

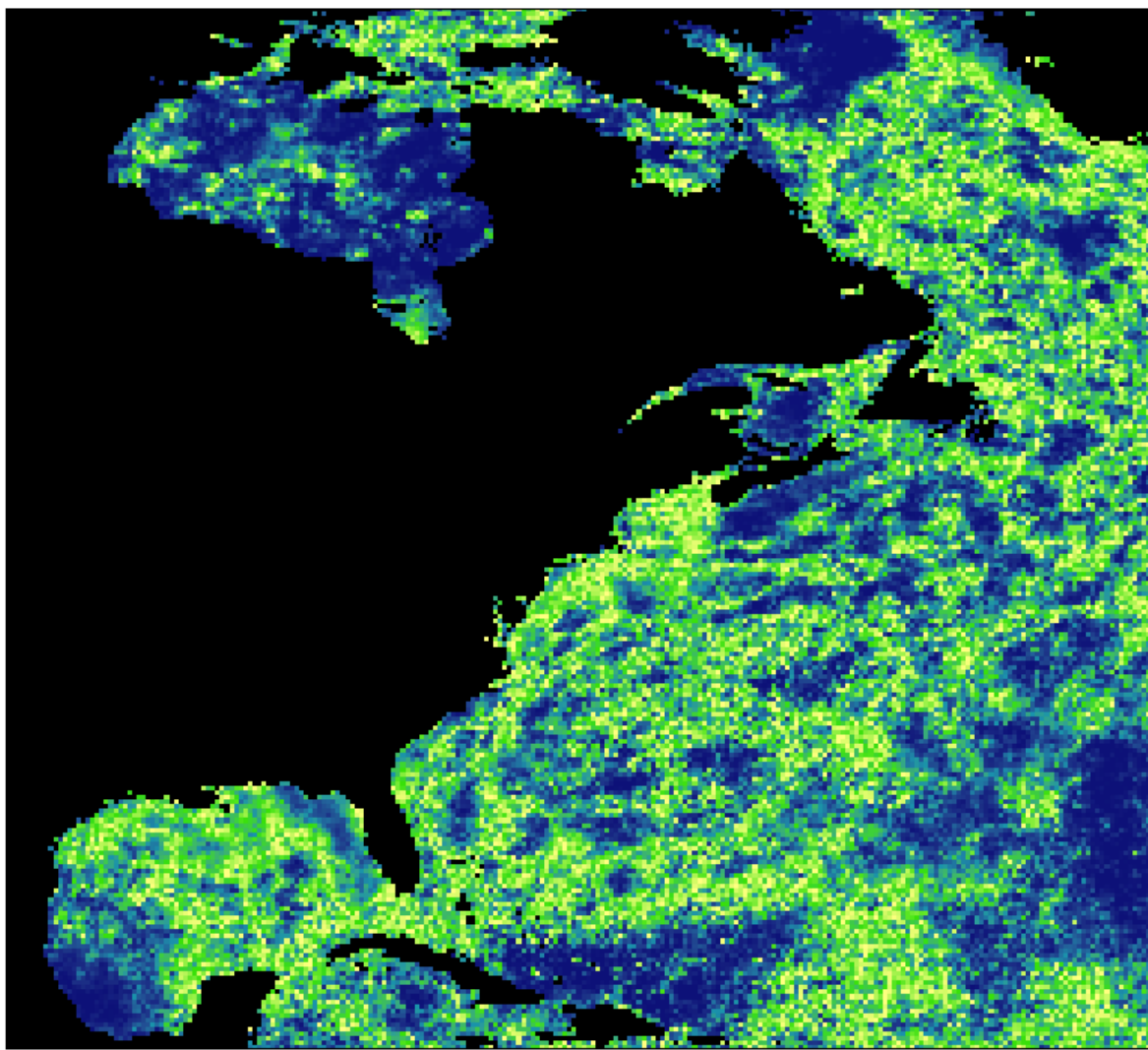


## April NAO v. October SST

R Squared

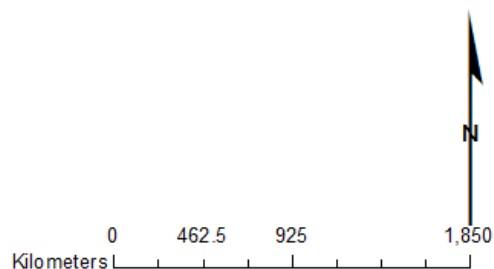
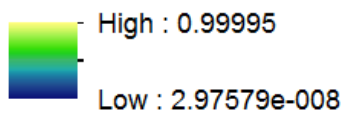


Ana Griefen 2014  
WGS 1984



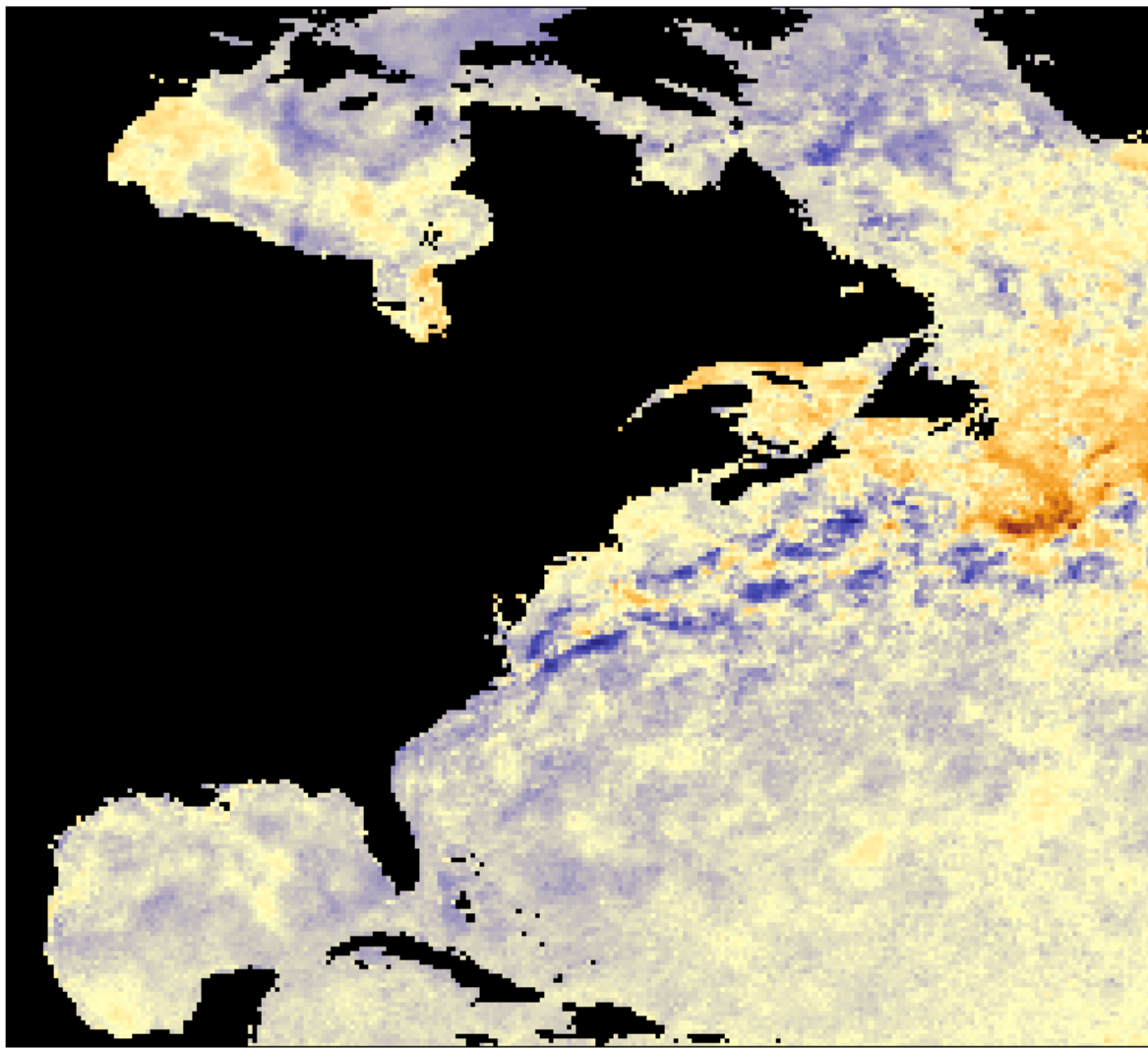
## April NAO v. October SST

P Value



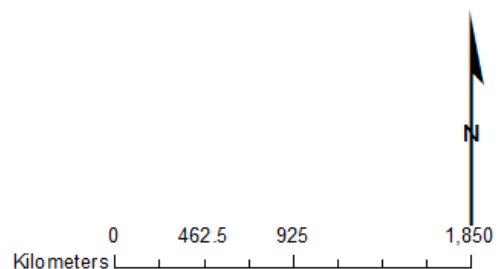
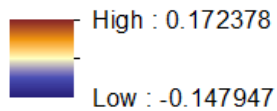
Ana Griefen 2014  
WGS 1984





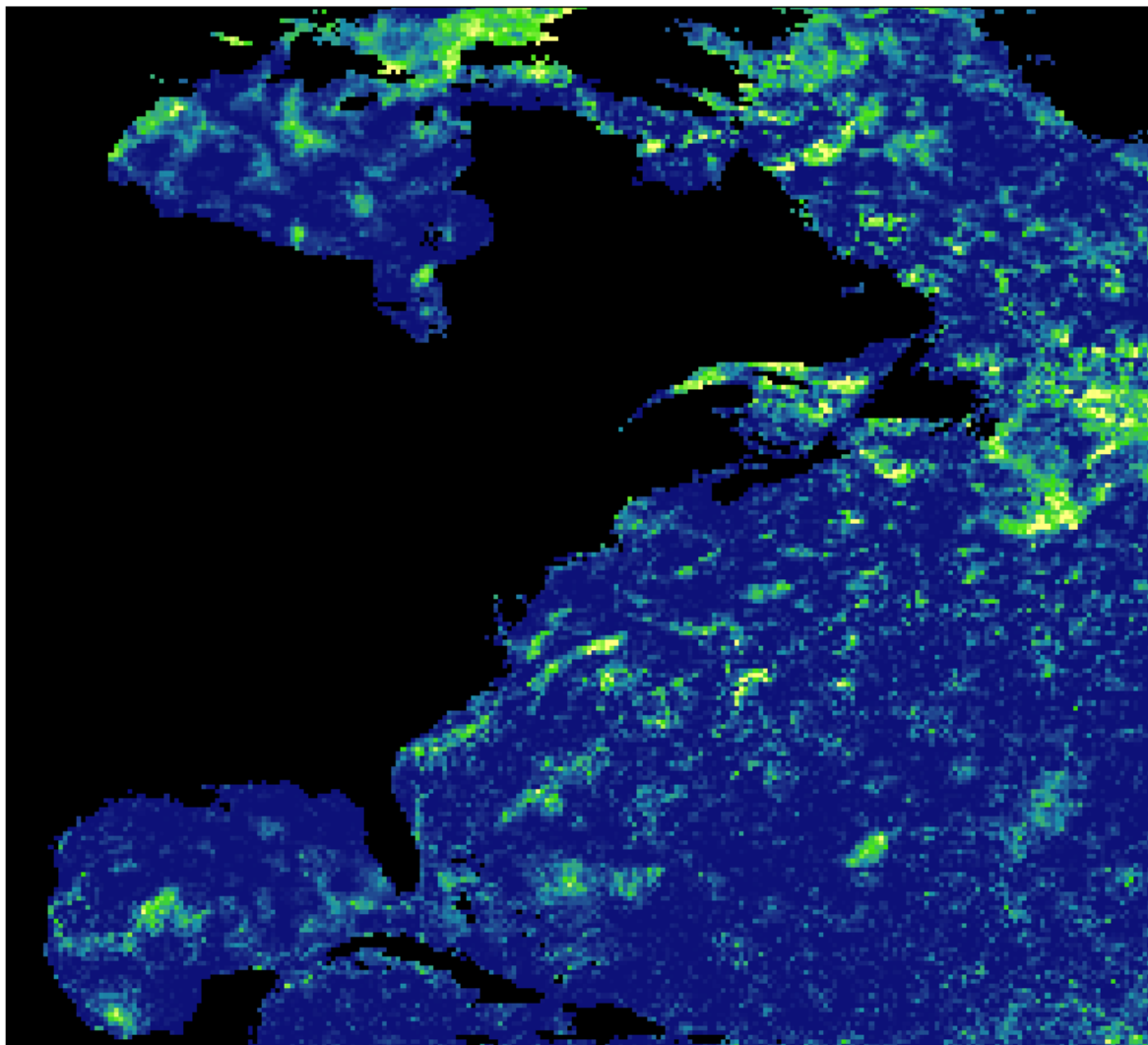
## November NAO v. November SST

Regression Coefficient



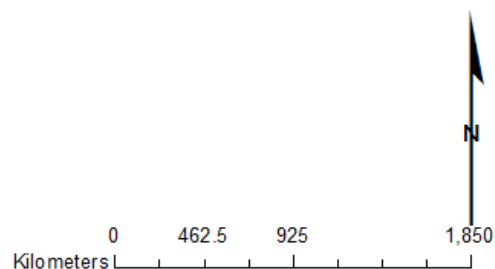
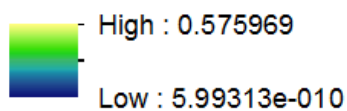
Ana Griefen 2014  
WGS 1984



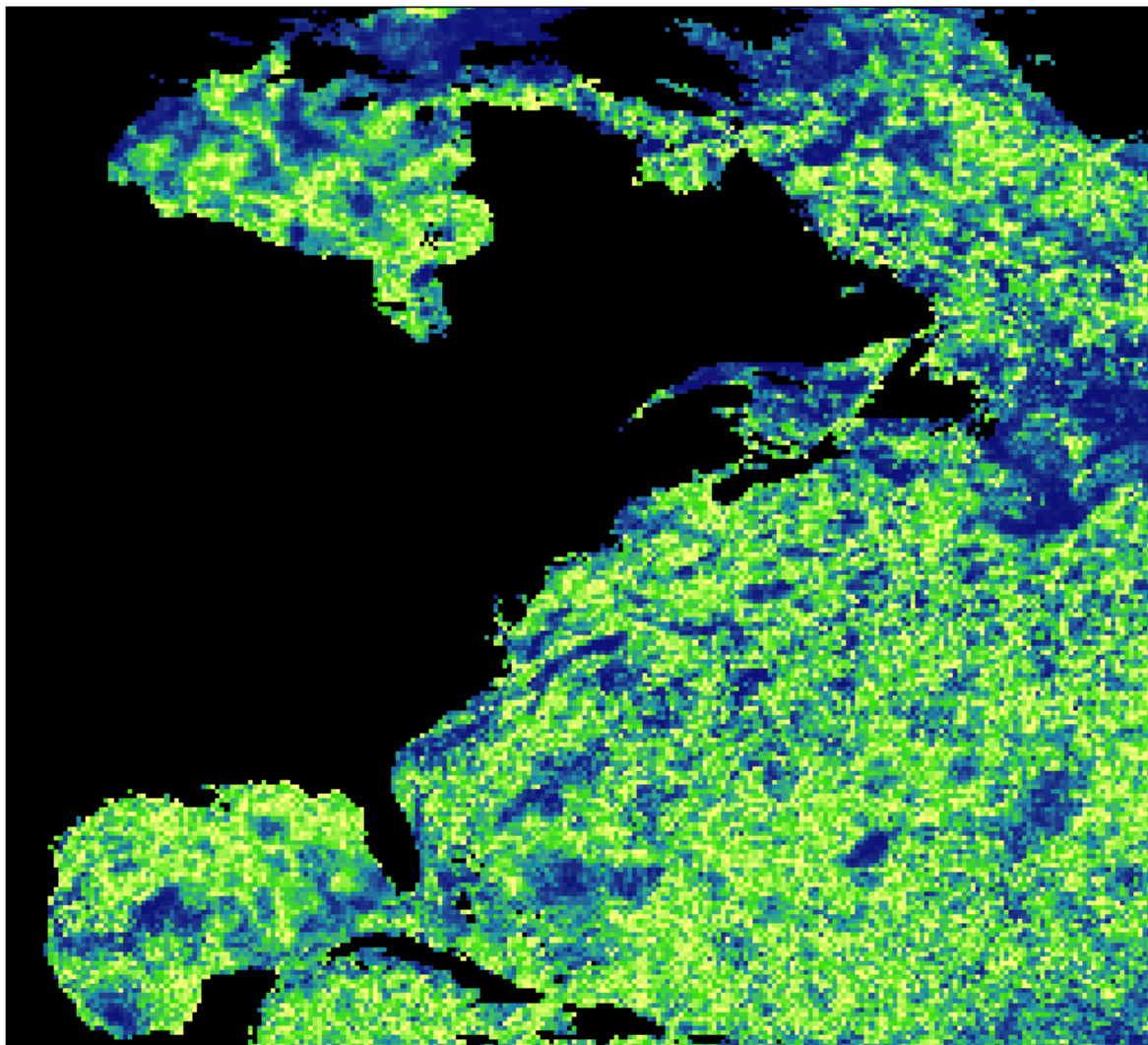


## November NAO v. November SST

R Squared

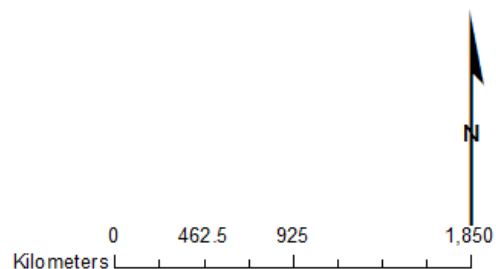
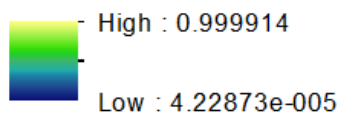


Ana Griefen 2014  
WGS 1984

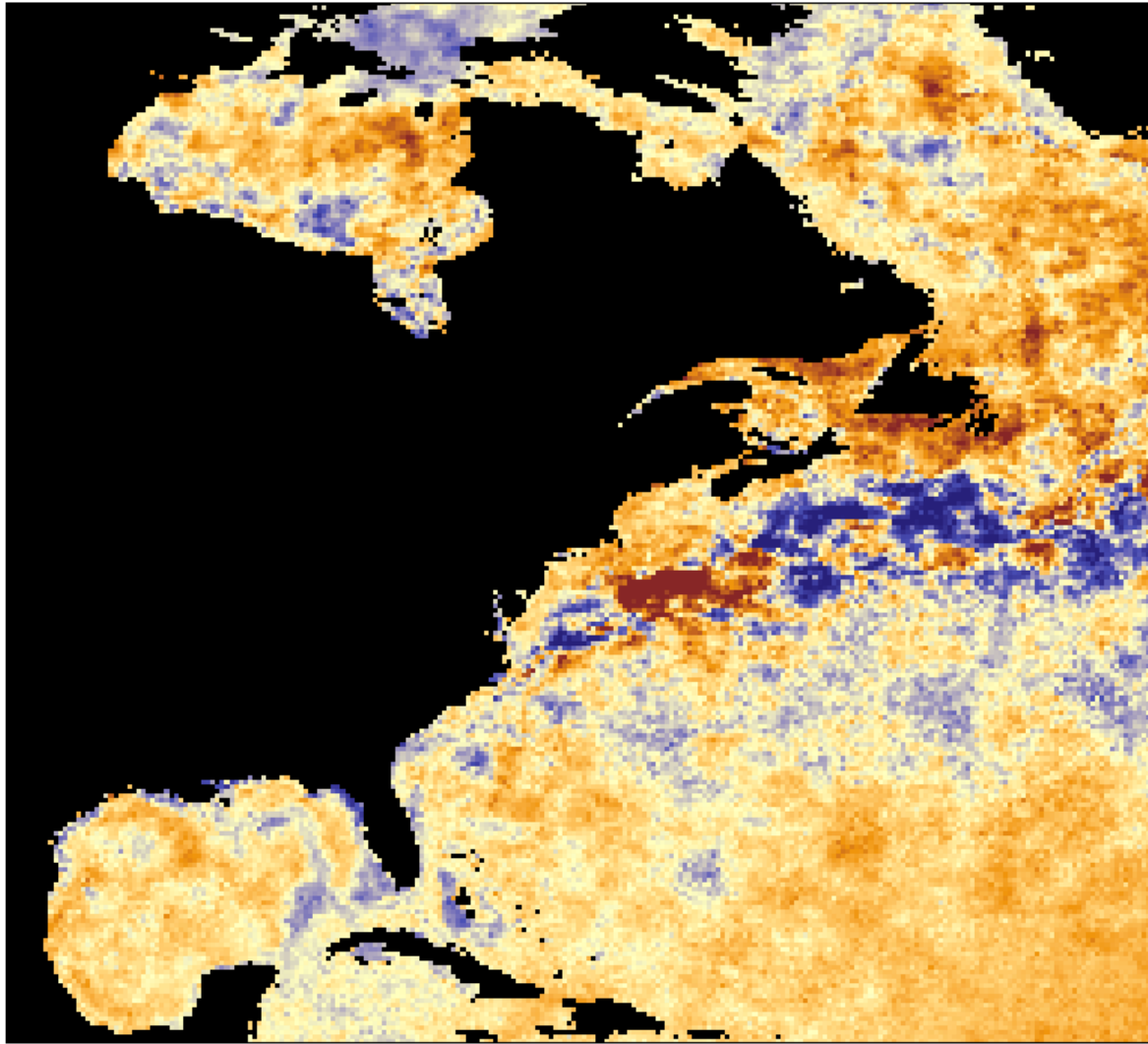


## November NAO v. November SST

P Value

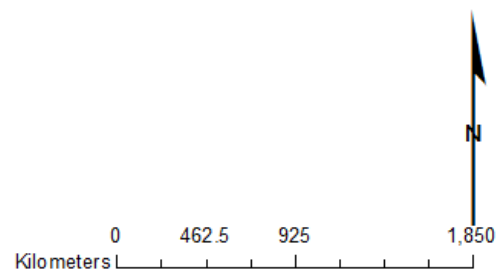
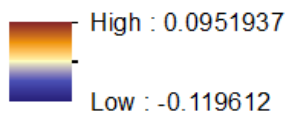


Ana Griefen 2014  
WGS 1984

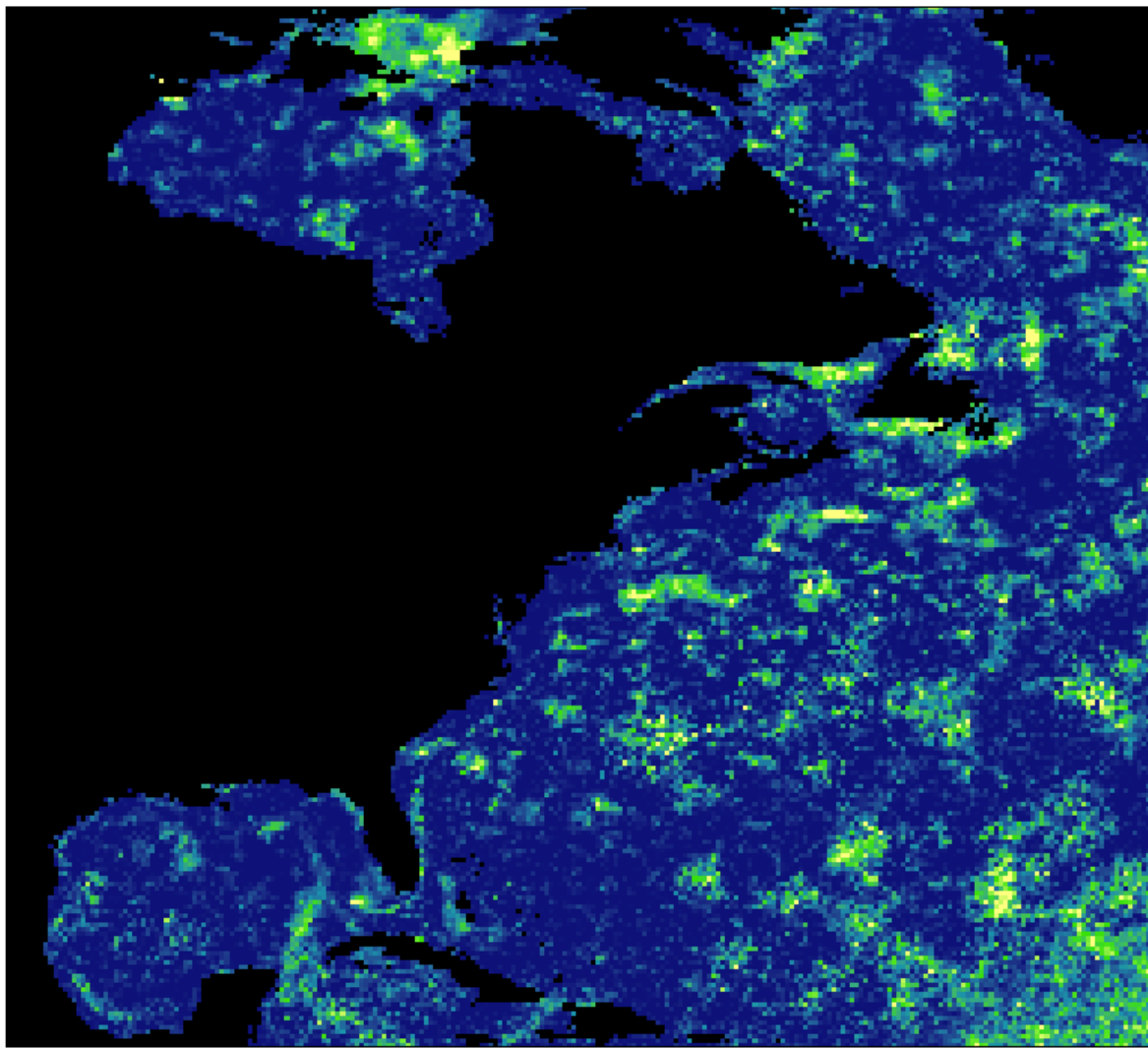


## May NAO v. November SST

Regression Coefficient

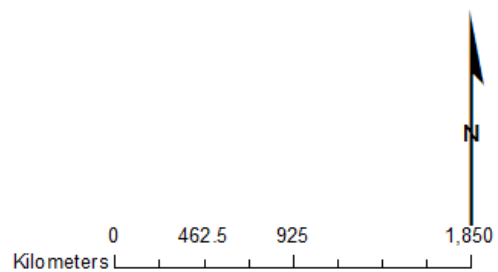
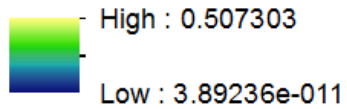


Ana Griefen 2014  
WGS 1984

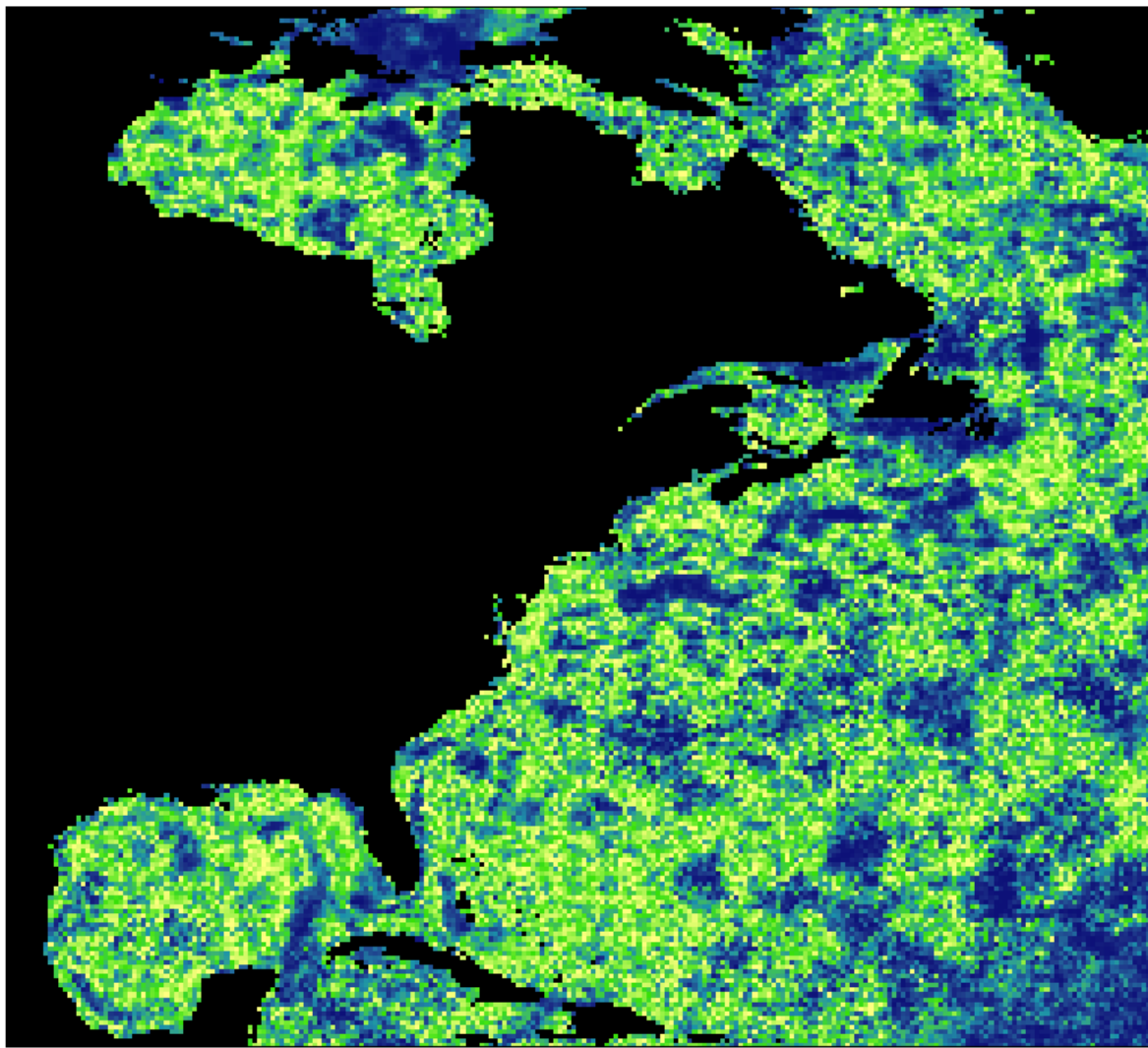


## May NAO v. November SST

R Squared

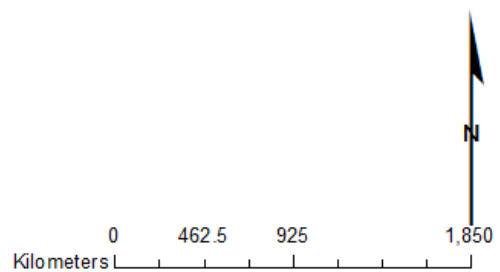
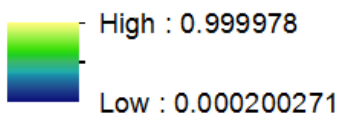


Ana Griefen 2014  
WGS 1984

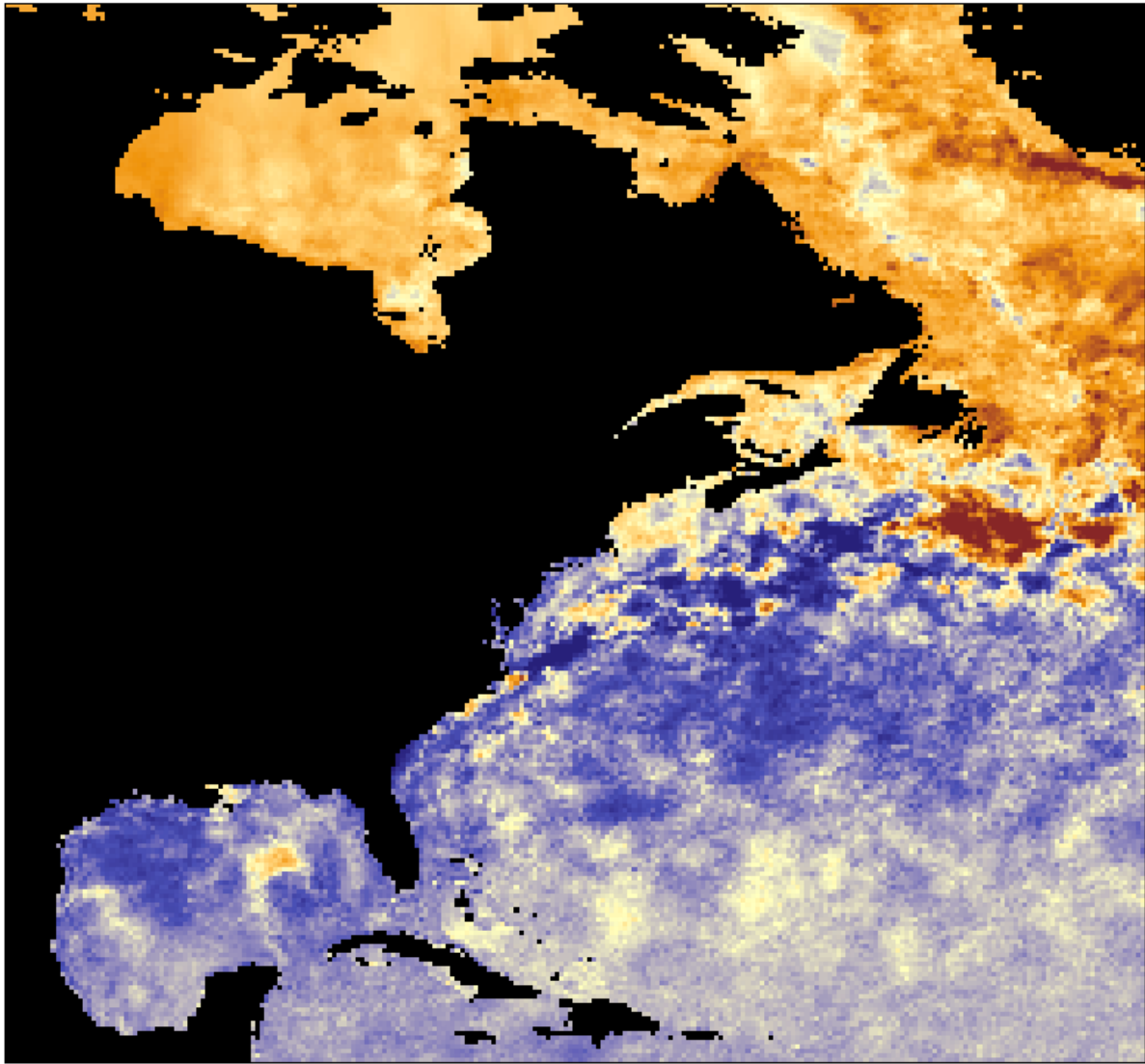


## May NAO v. November SST

P Value

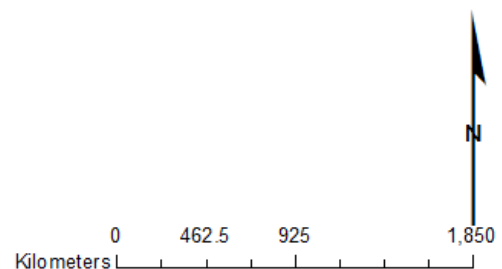
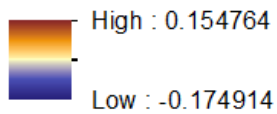


Ana Griefen 2014  
WGS 1984

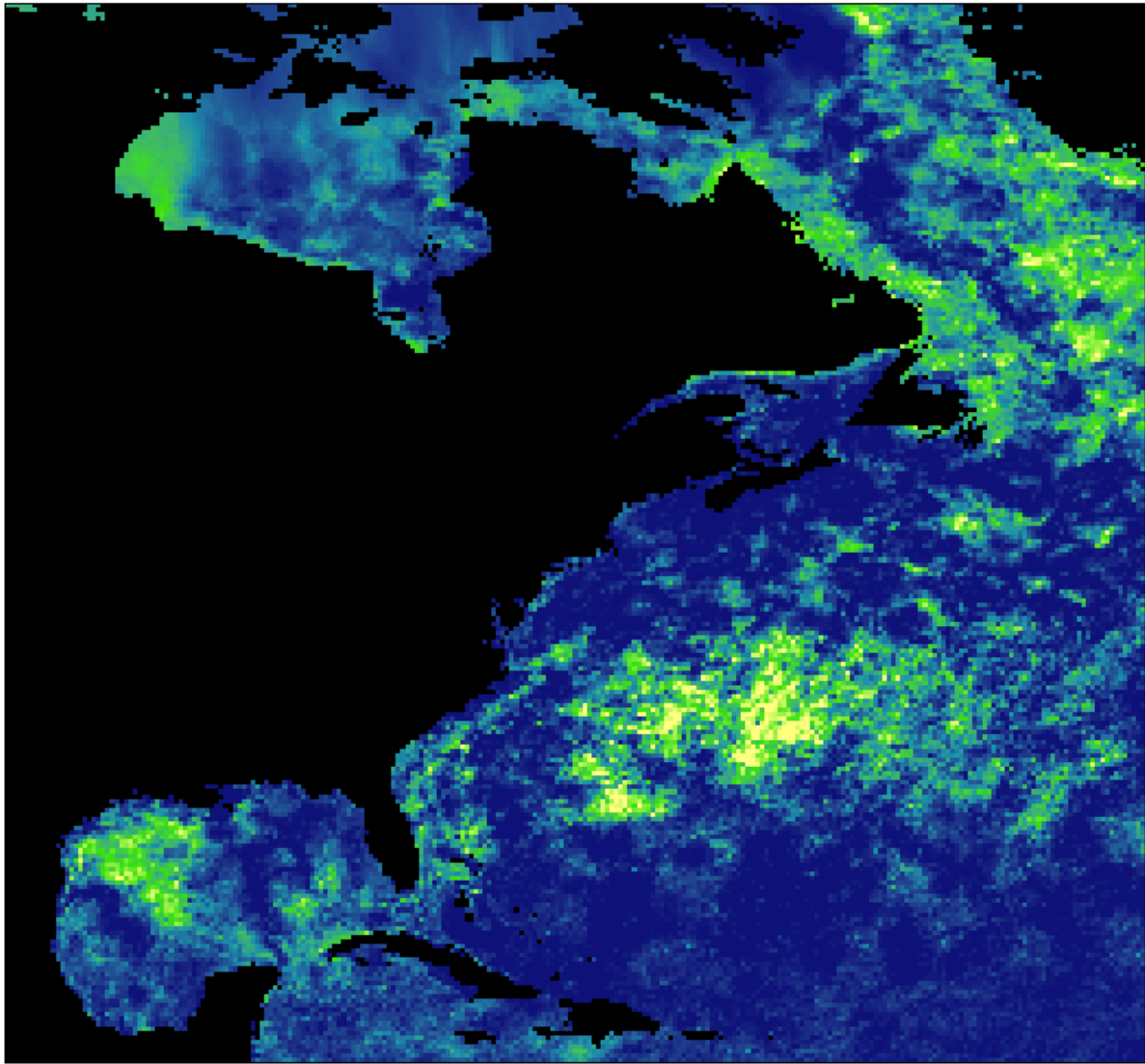


## December NAO v. December SST

Regression Coefficient



Ana Griefen 2014  
WGS 1984



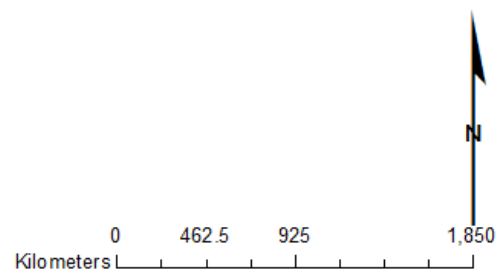
## December NAO v. December SST

R Squared



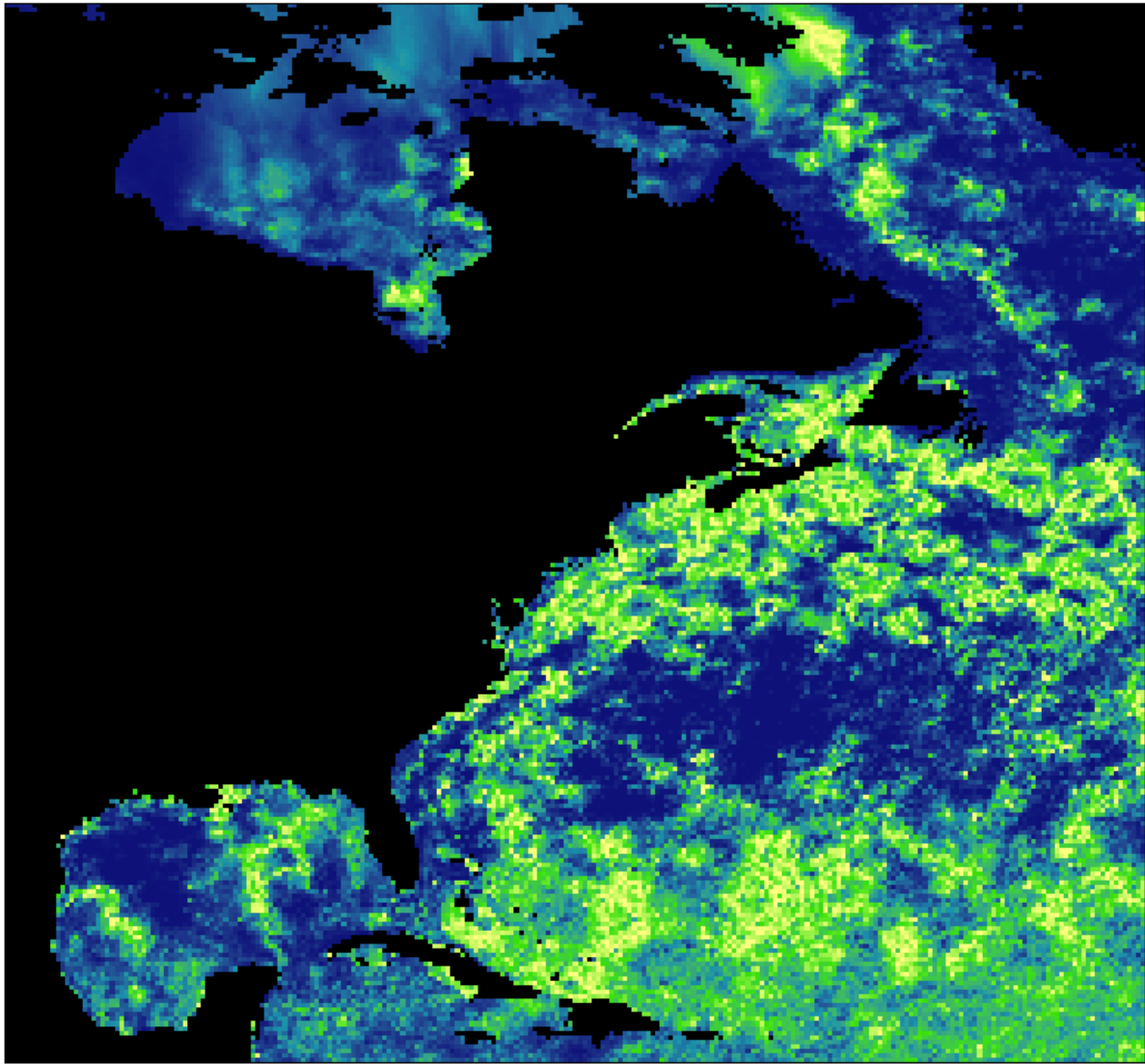
High : 0.666409

Low : 9.06814e-010



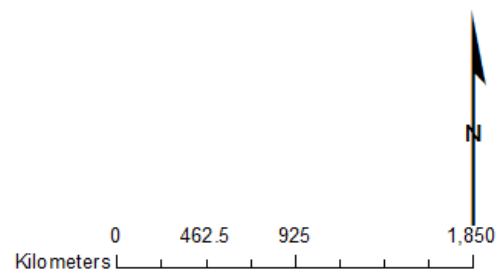
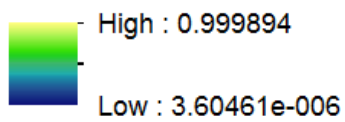
Ana Griefen 2014  
WGS 1984





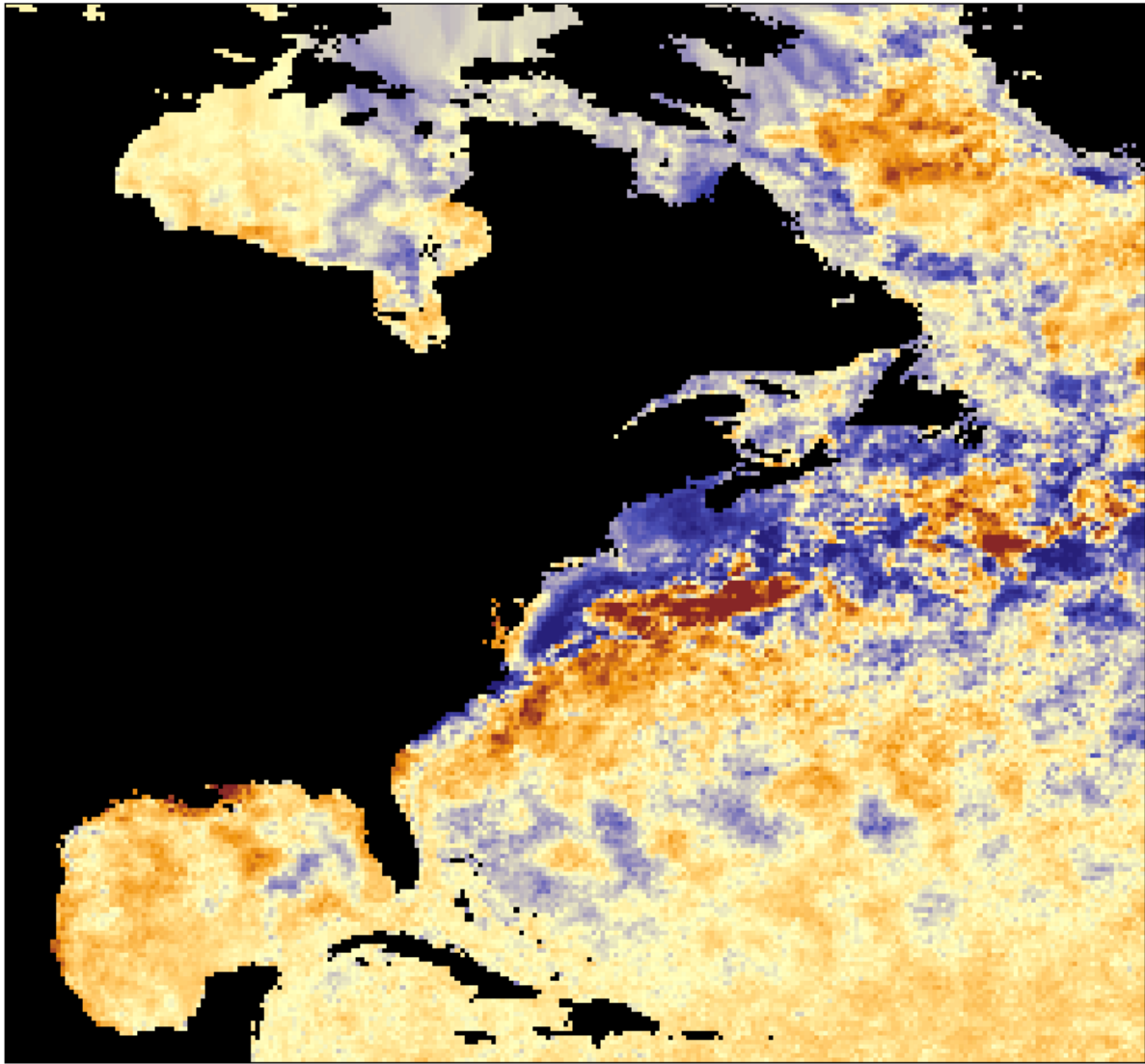
## December NAO v. December SST

P Value



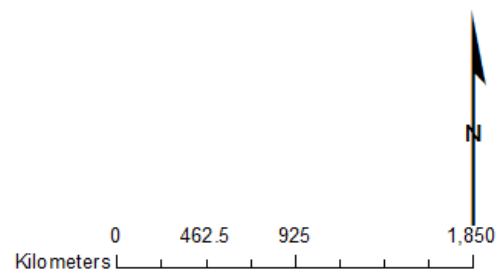
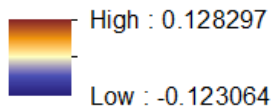
Ana Griefen 2014  
WGS 1984



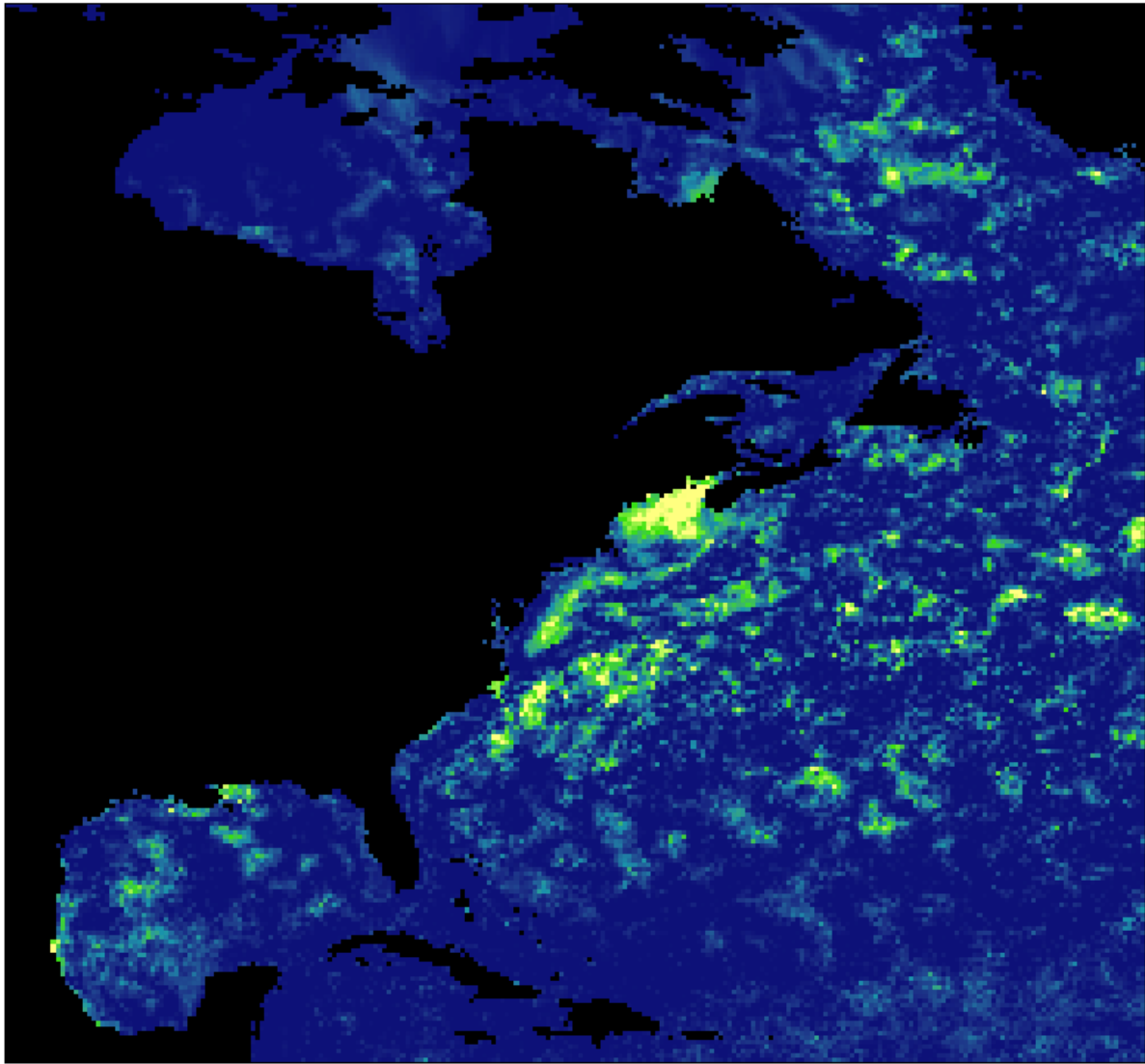


## June NAO v. December SST

Regression Coefficient



Ana Griefen 2014  
WGS 1984



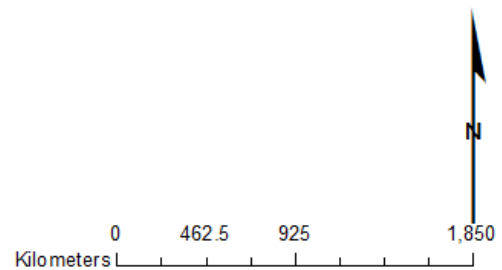
## June NAO v. December SST

R Squared

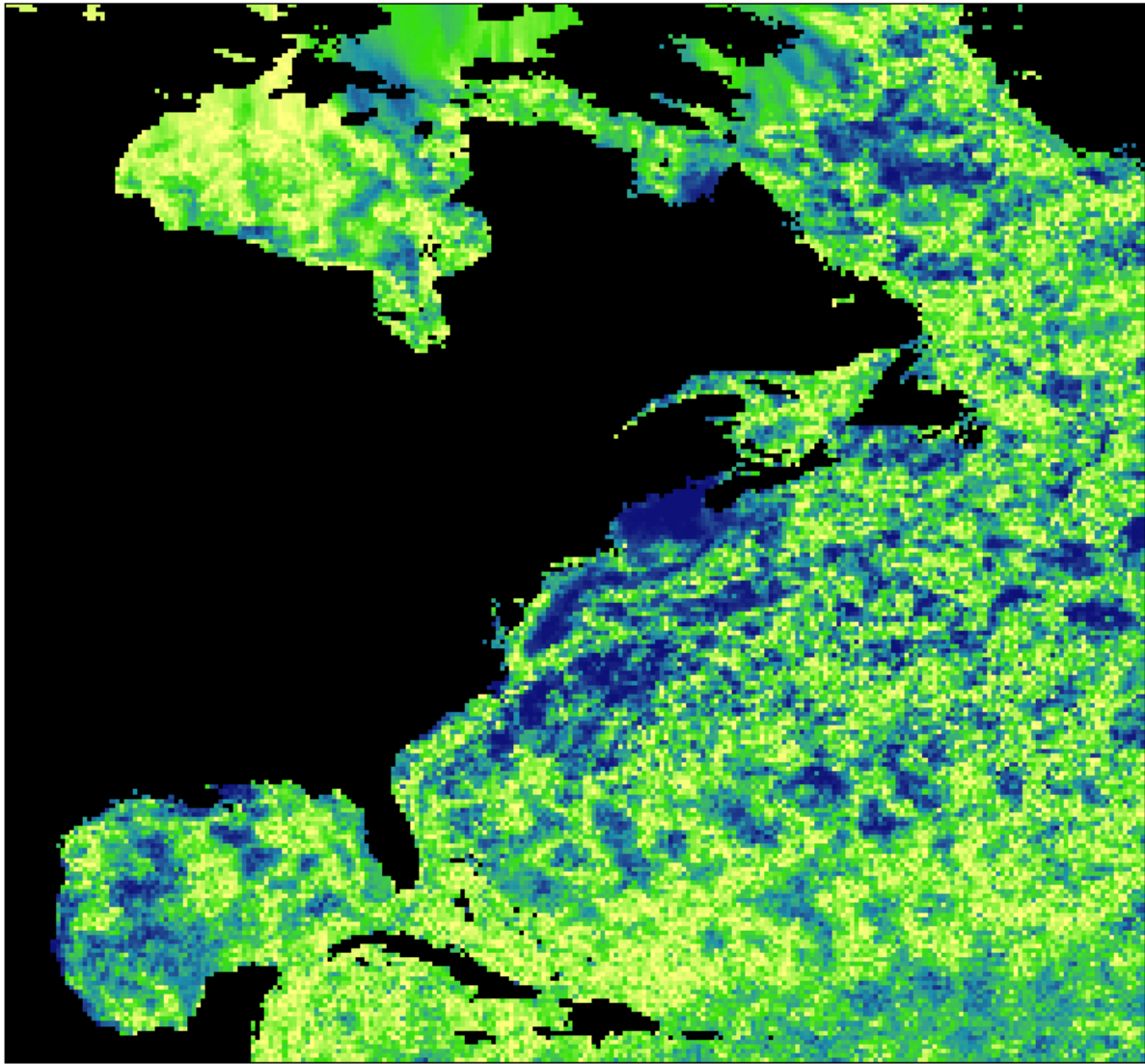


High : 0.483001

Low : 5.28981e-011

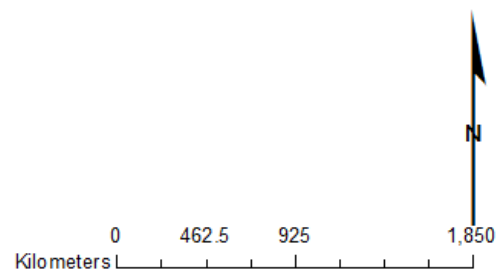
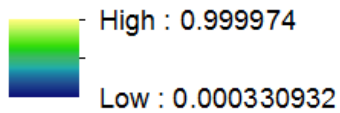


Ana Griefen 2014  
WGS 1984



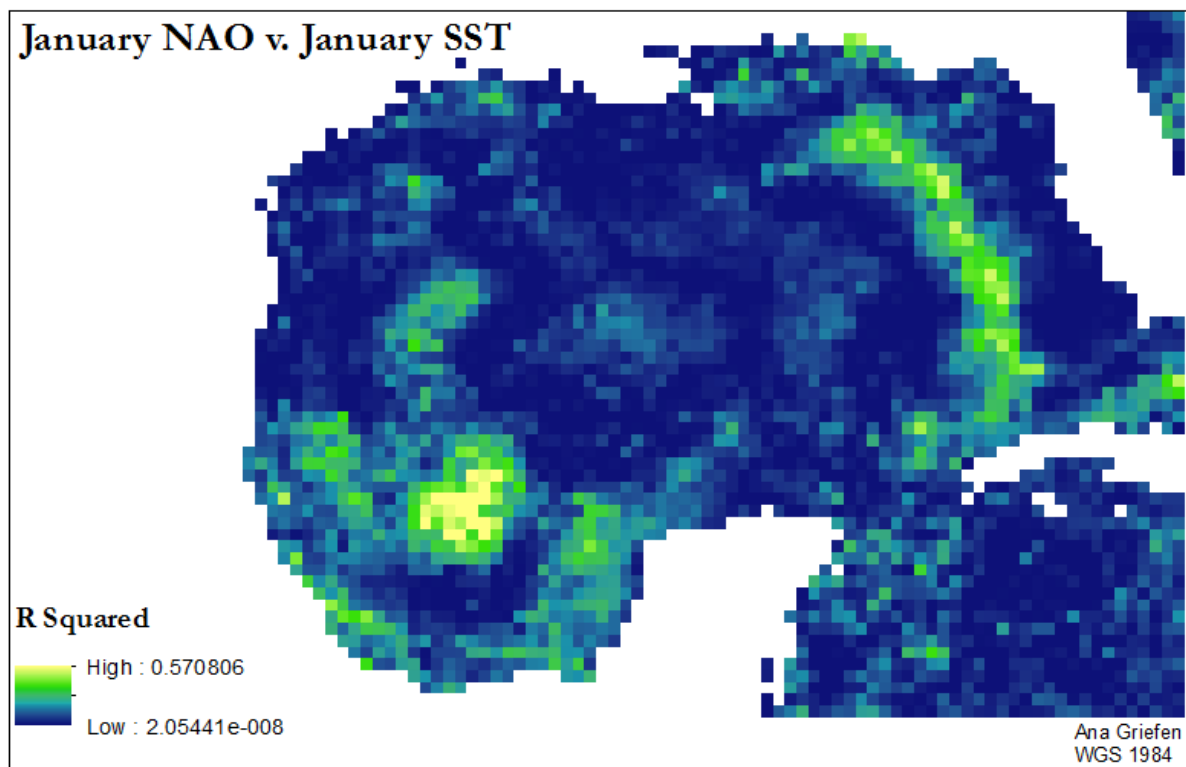
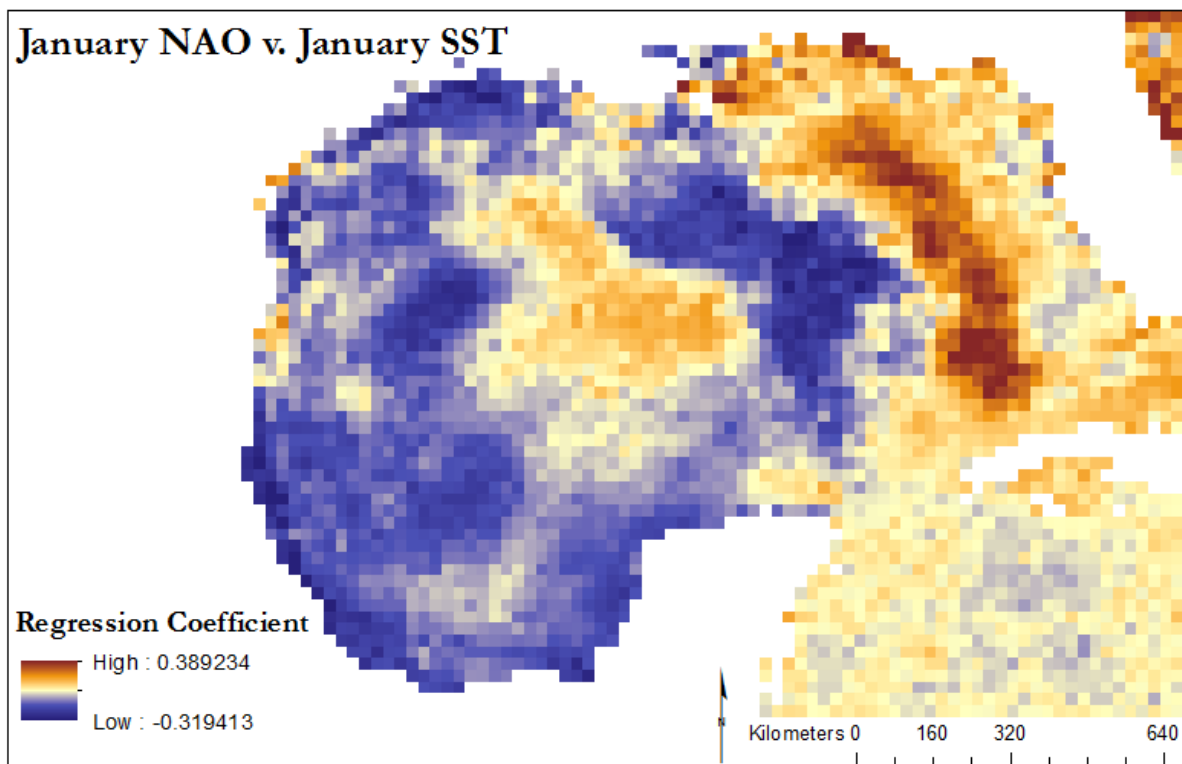
## June NAO v. December SST

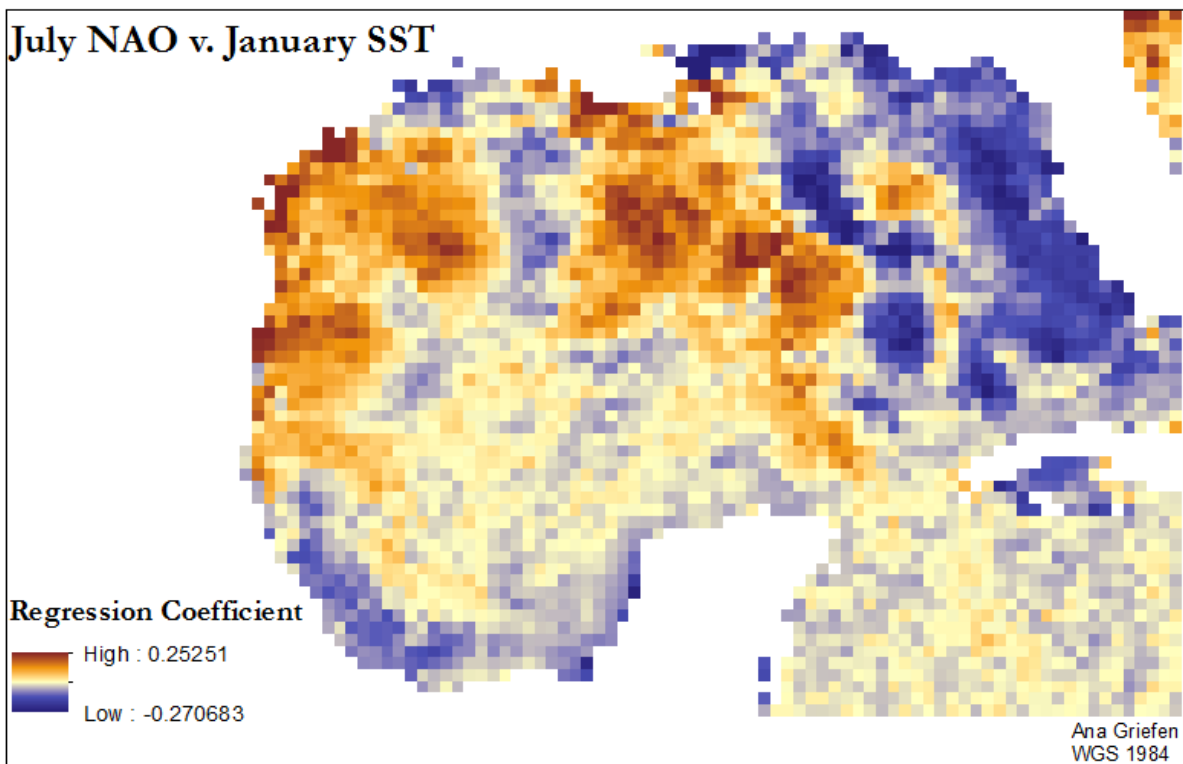
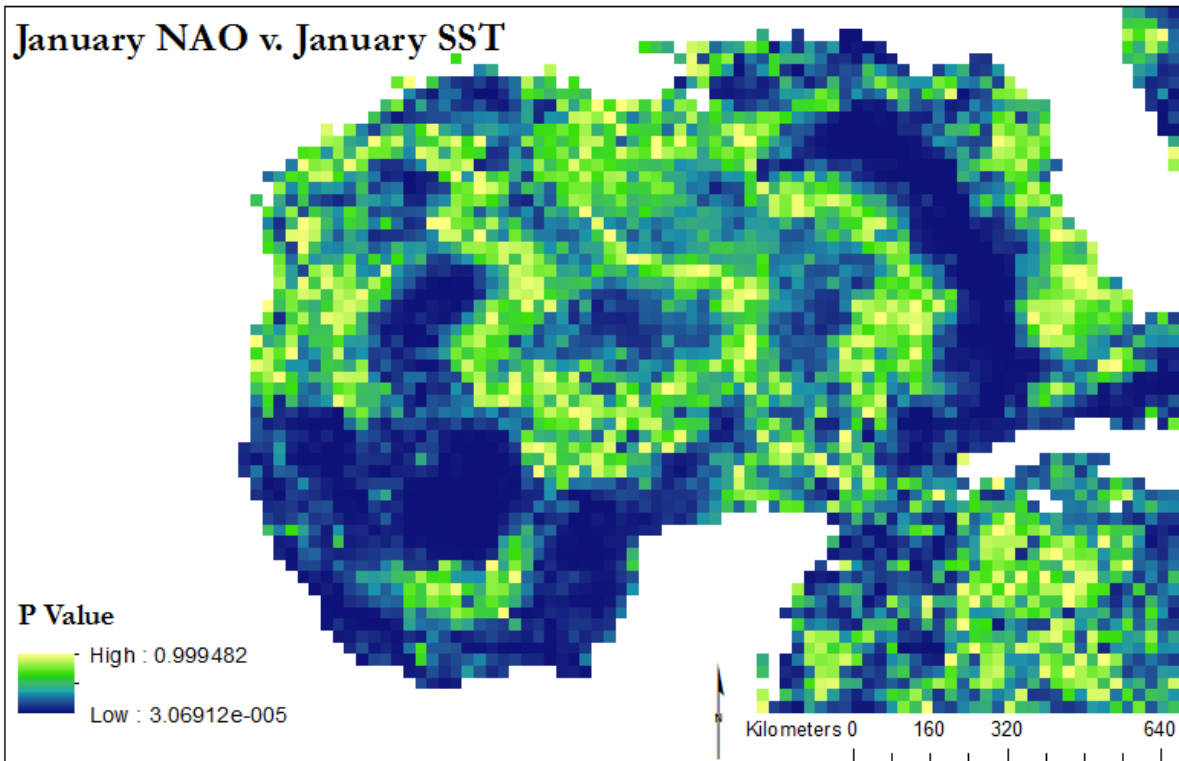
P Value

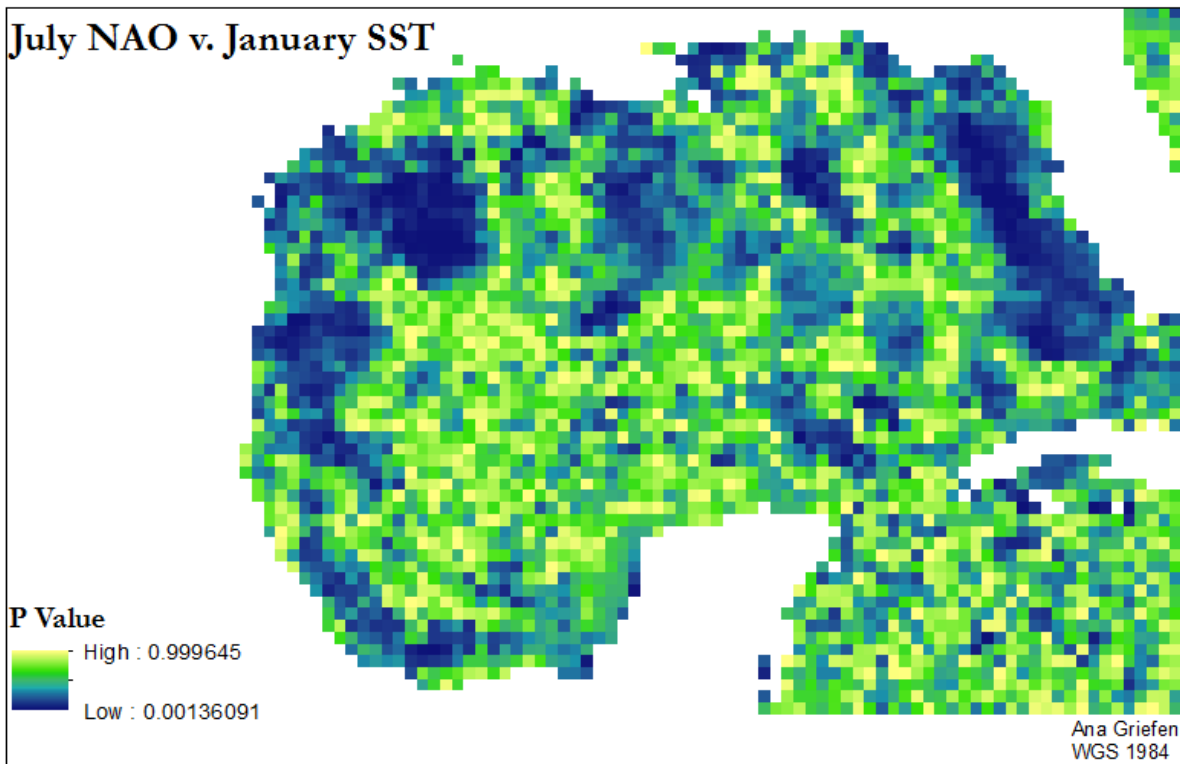
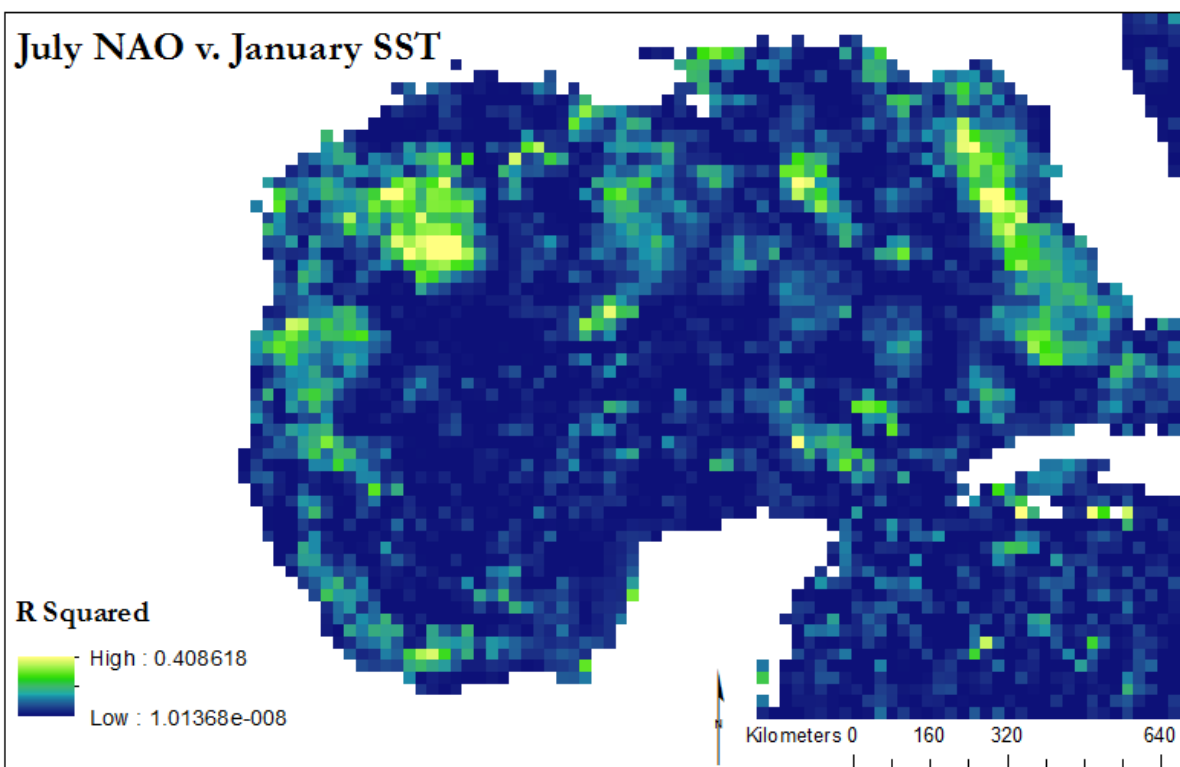


Ana Griefen 2014  
WGS 1984

## Appendix A.2 – Output raster surfaces – Gulf of Mexico

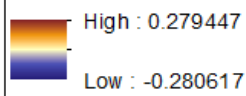






## February NAO v. February SST

Regression Coefficient



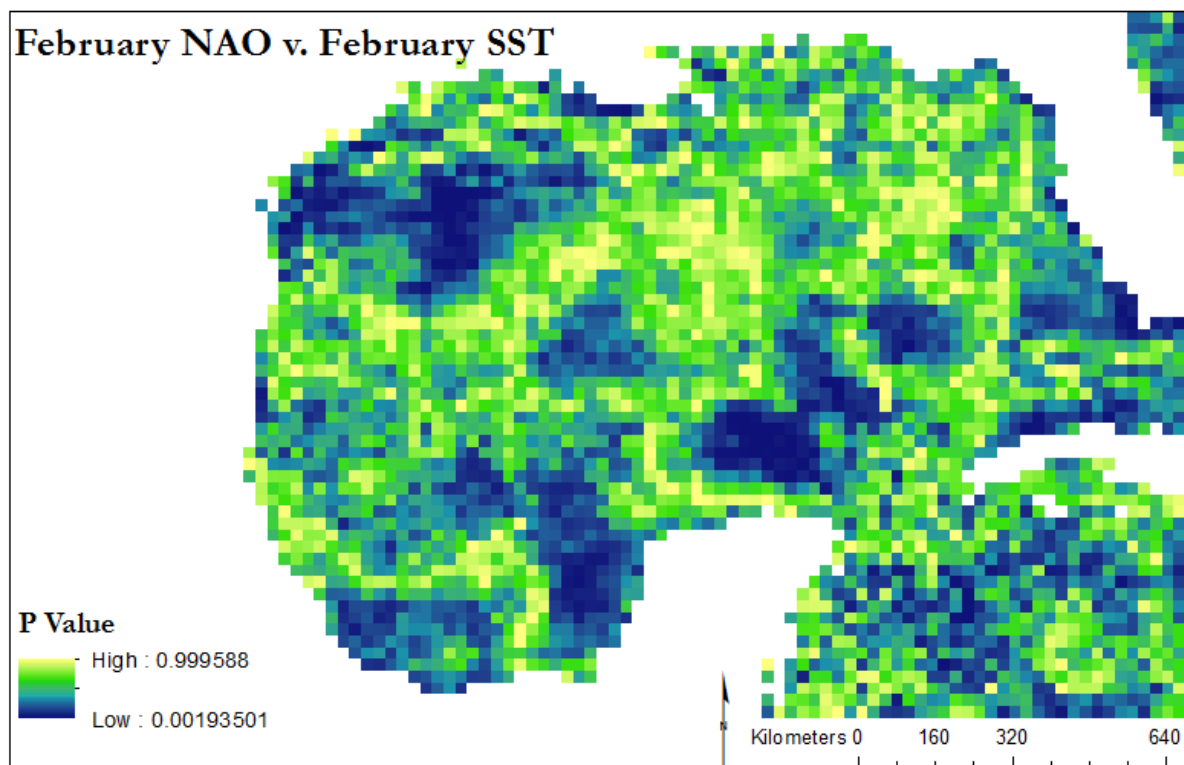
## February NAO v. February SST

R Squared

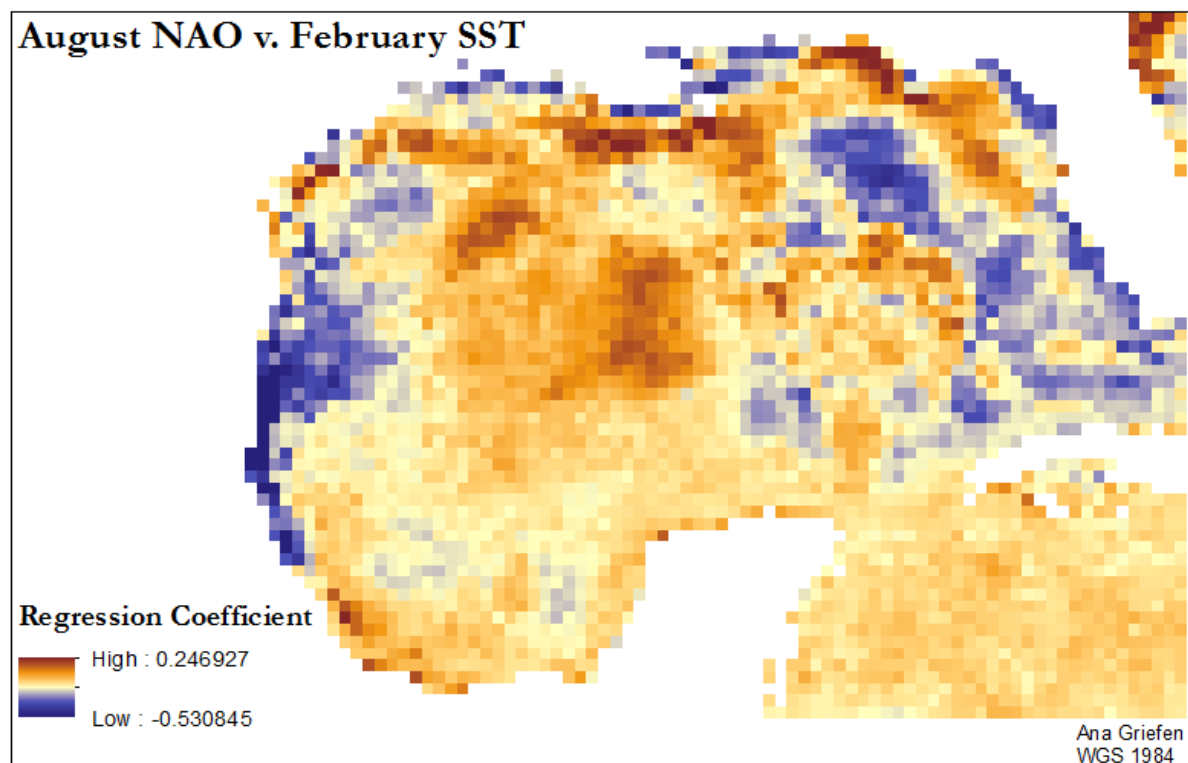


Ana Griefen  
WGS 1984

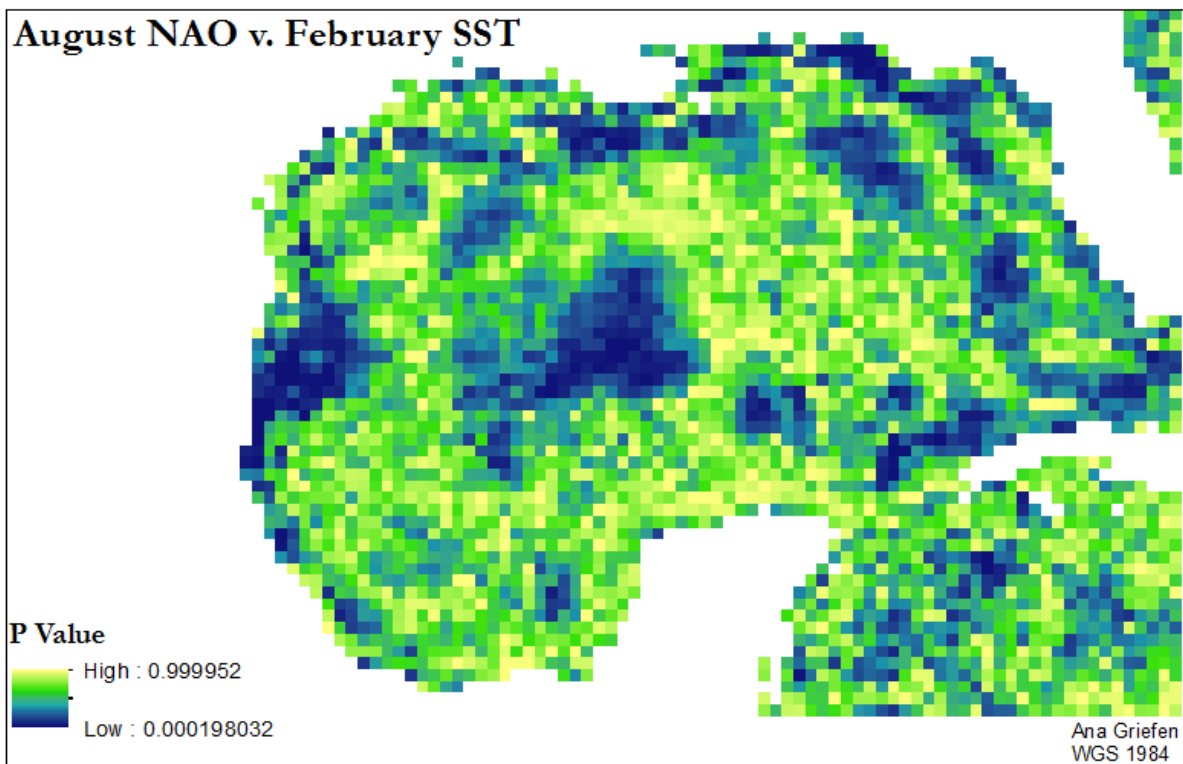
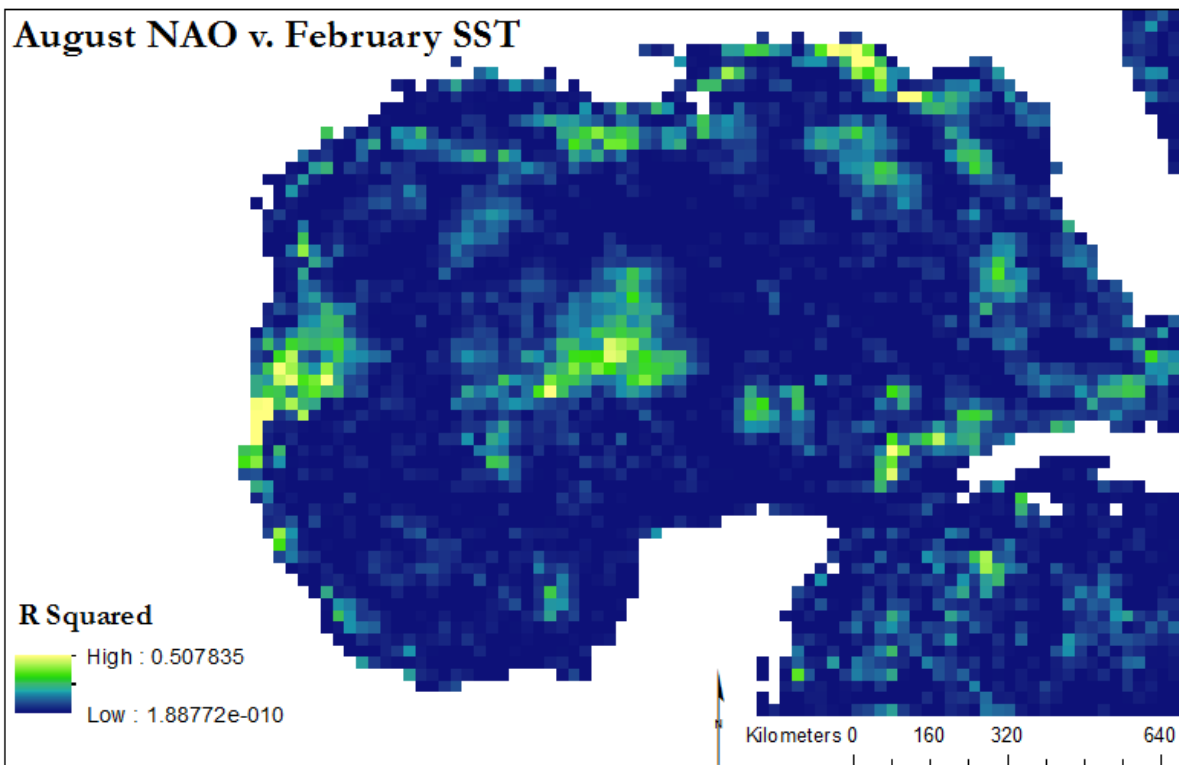
February NAO v. February SST

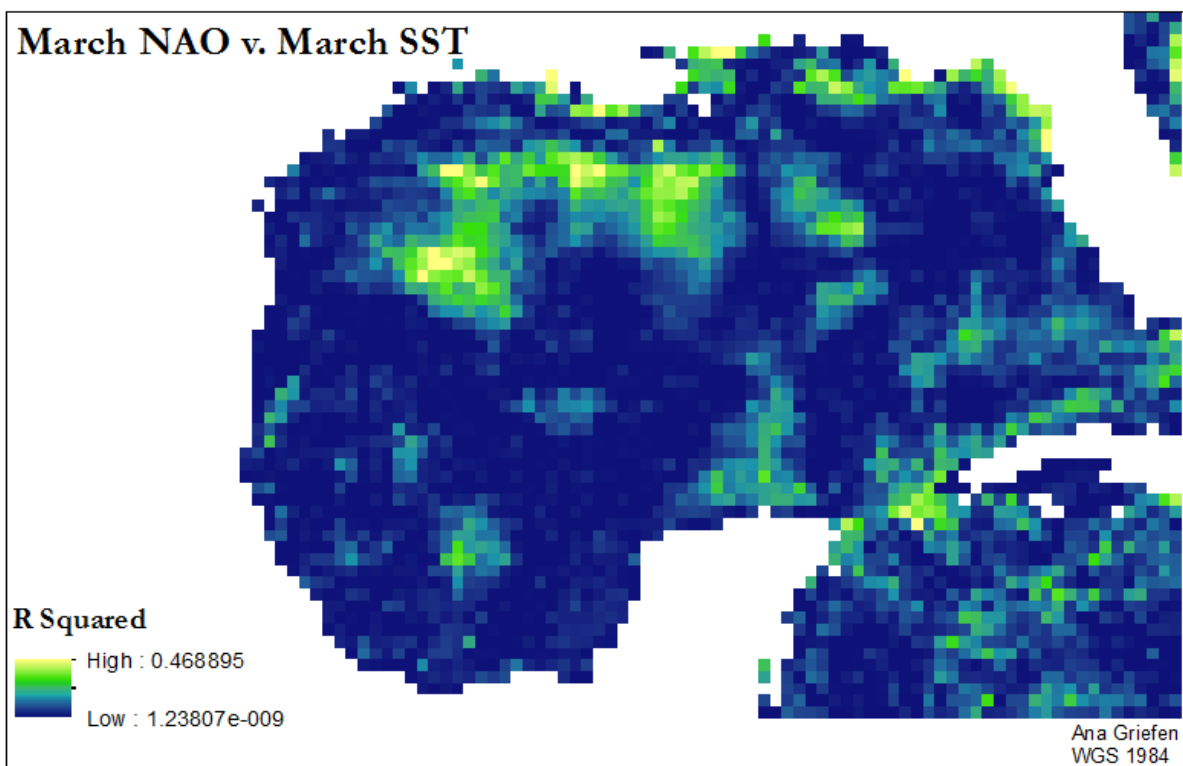
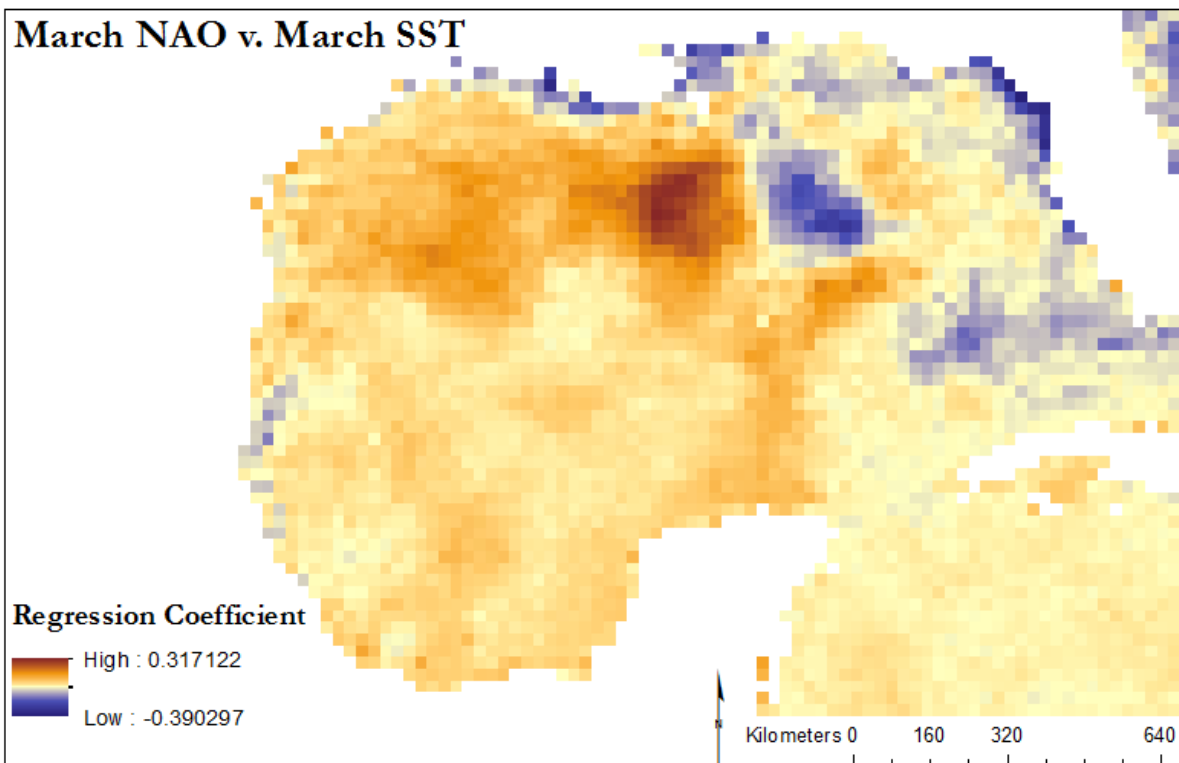


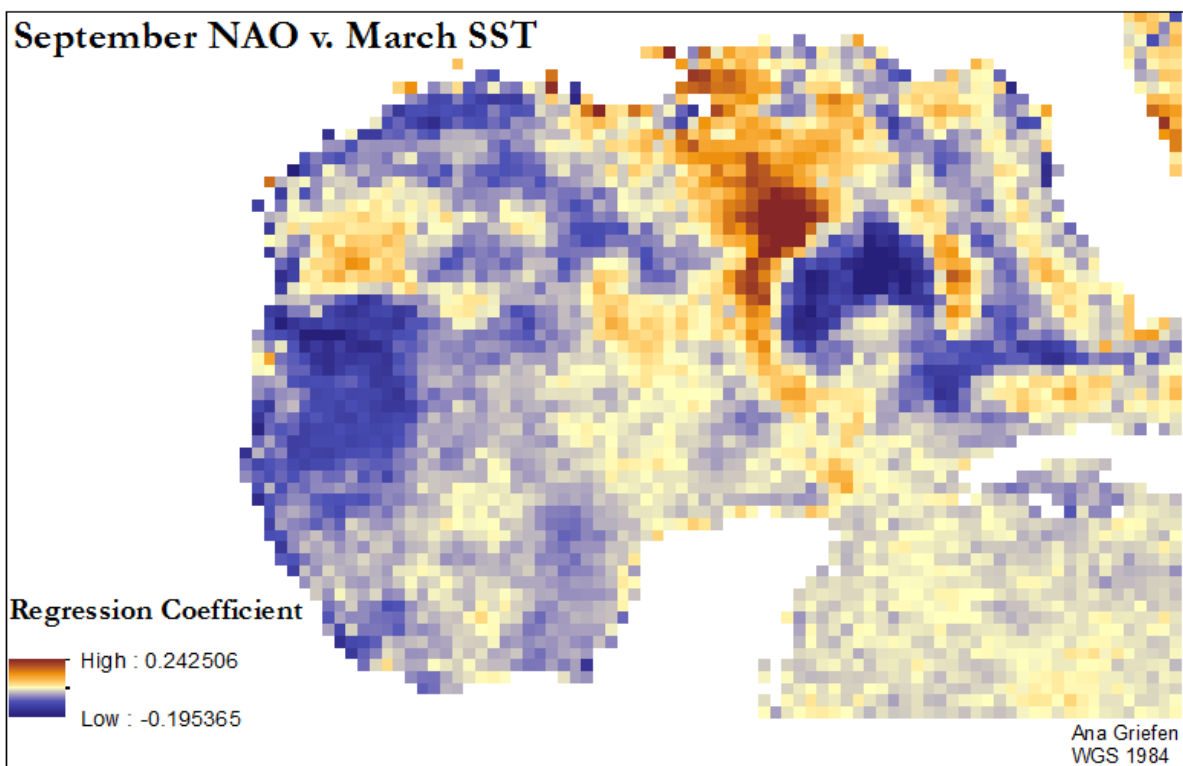
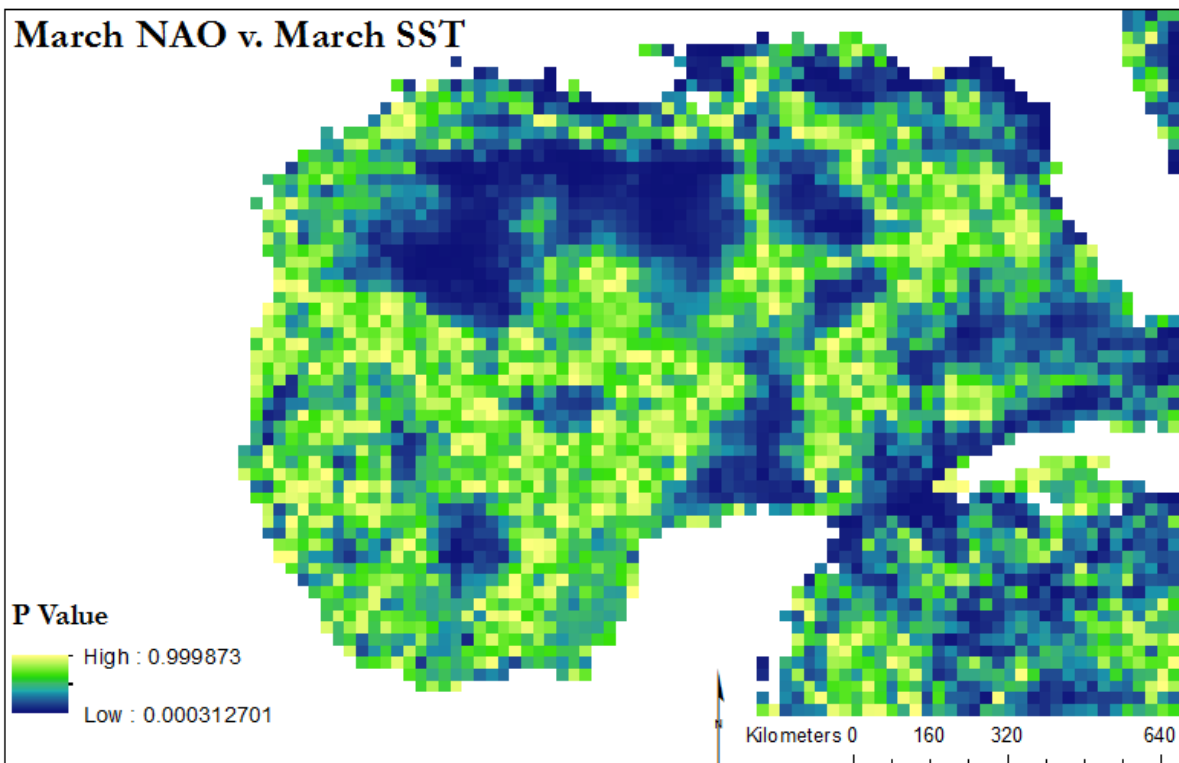
August NAO v. February SST

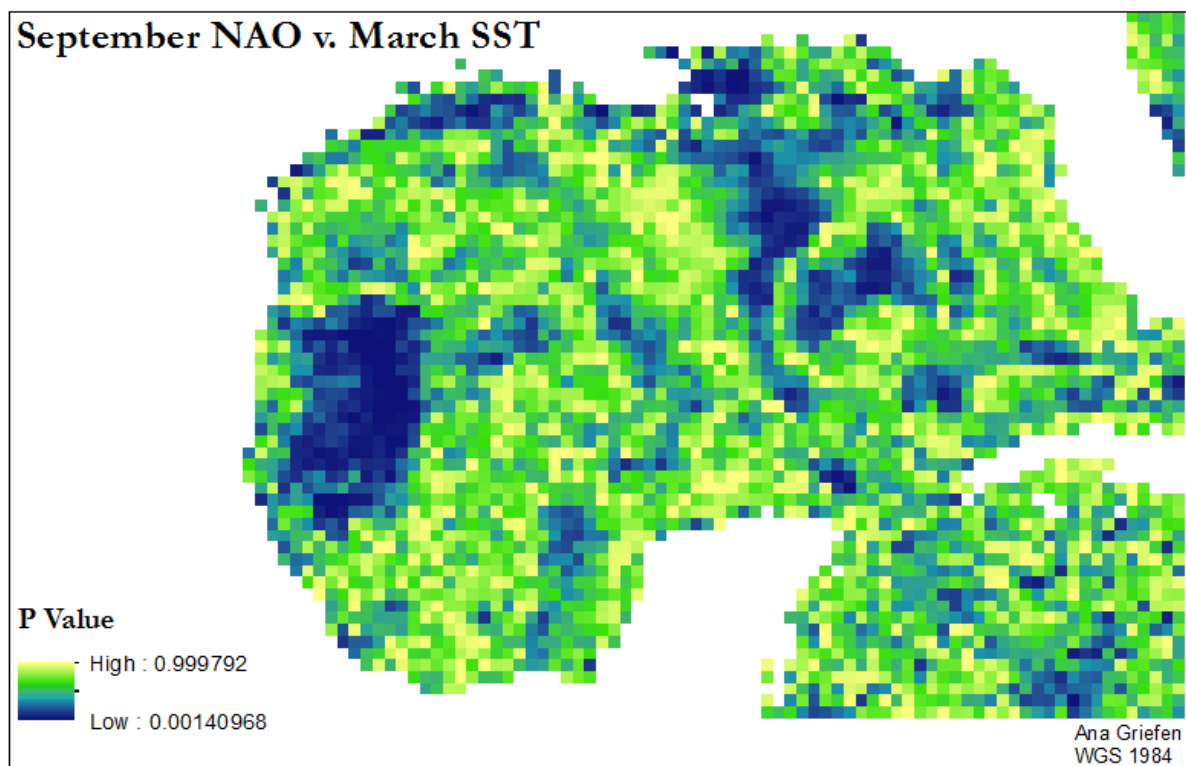
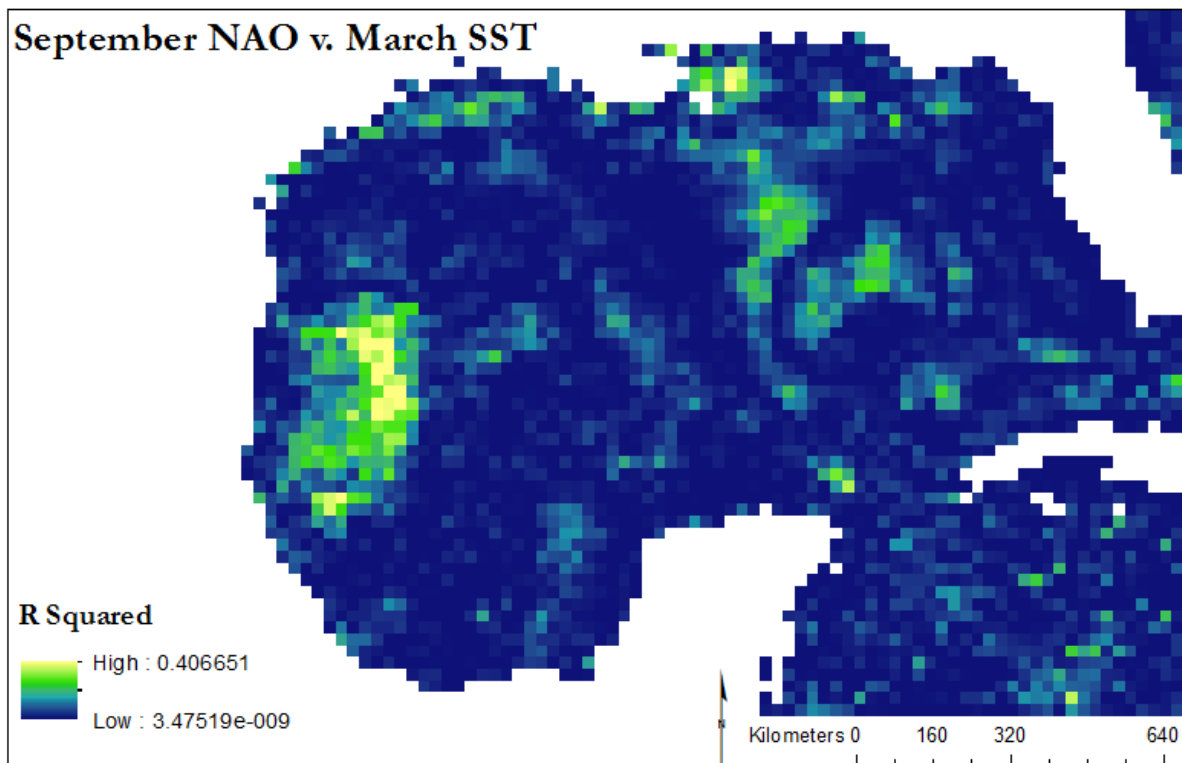


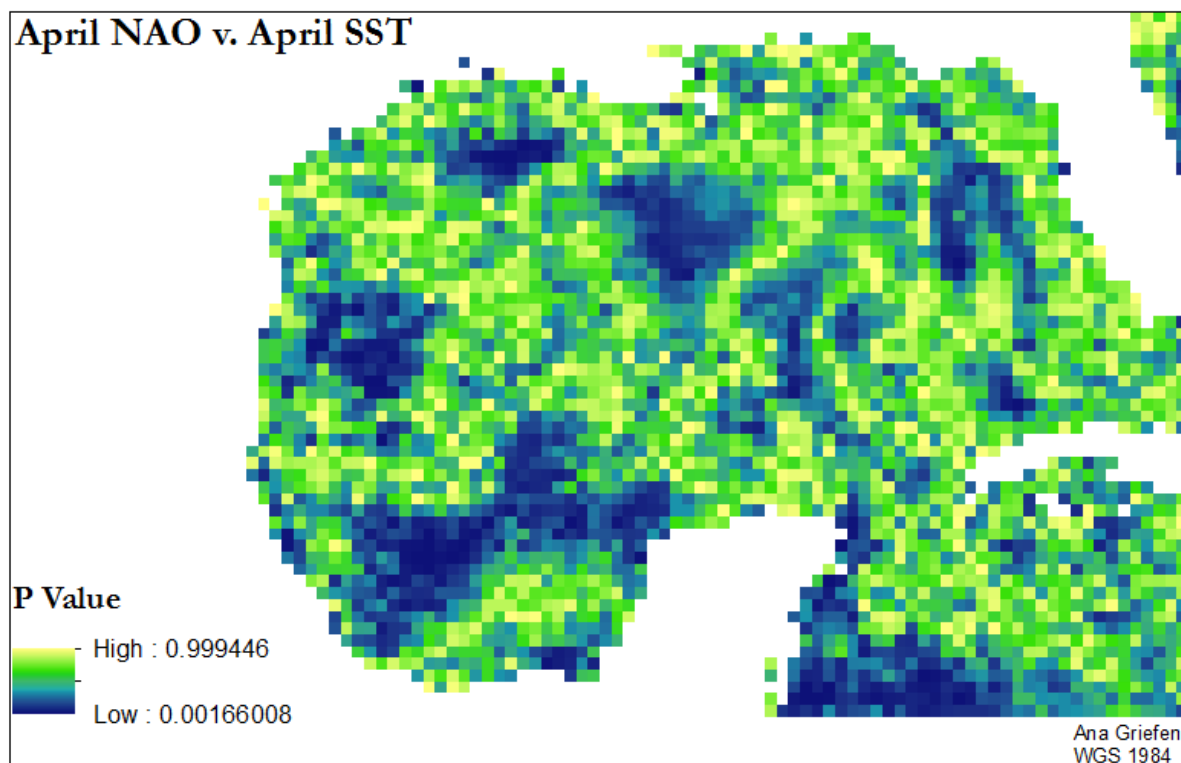
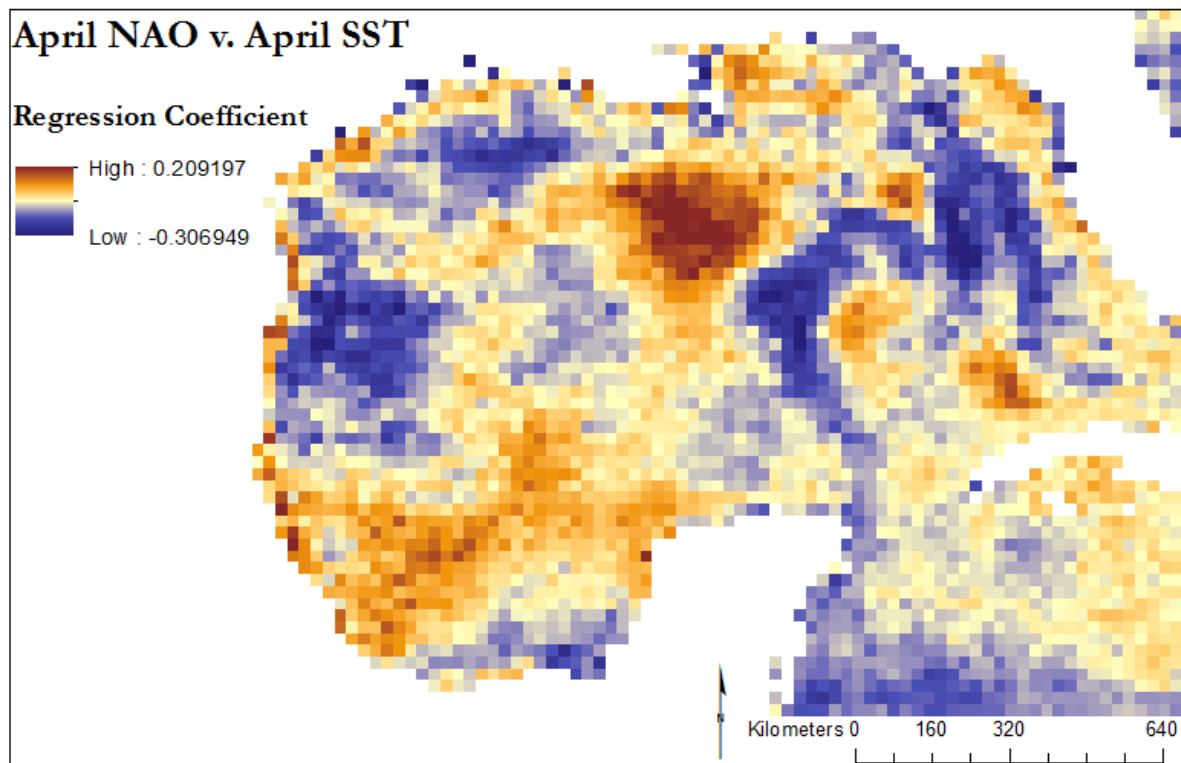


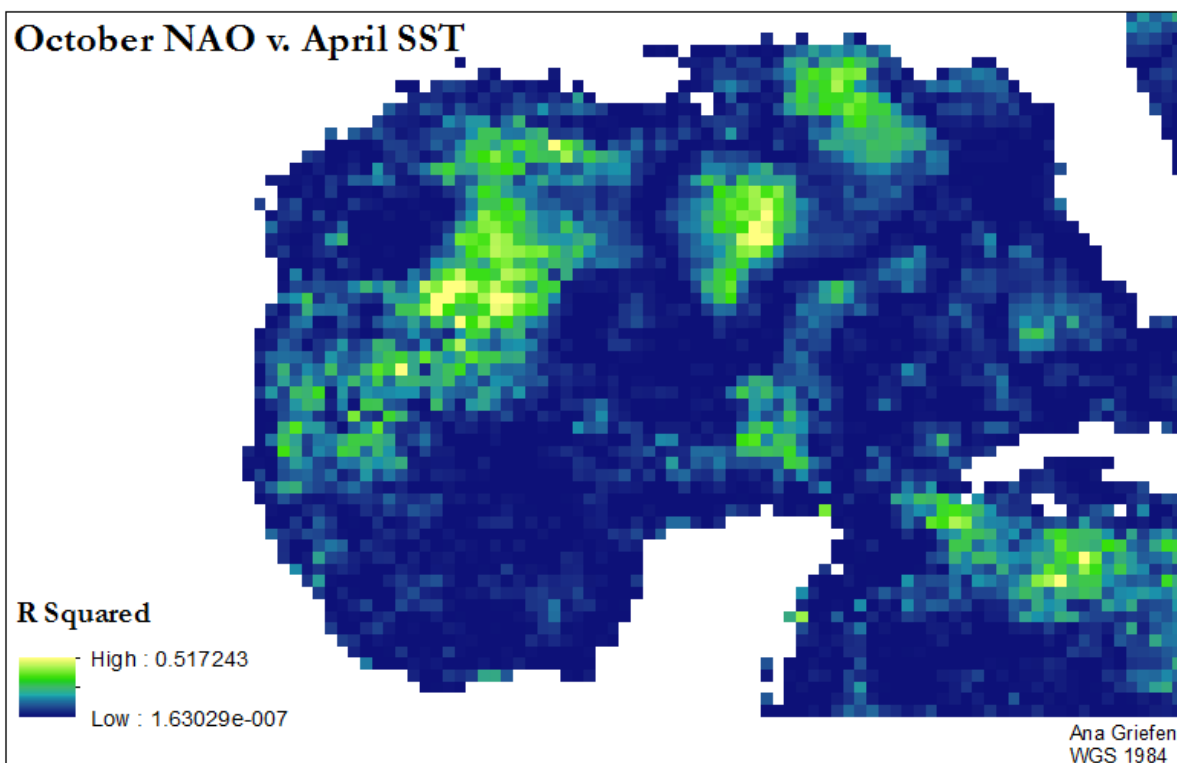
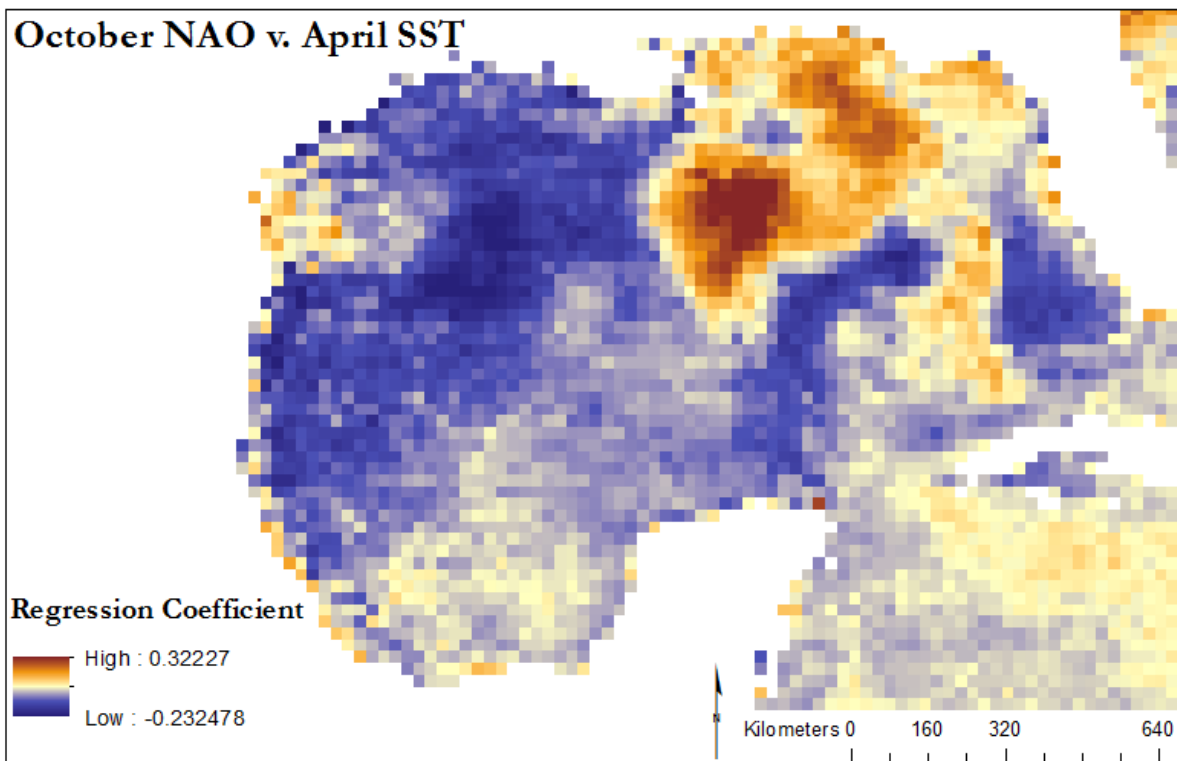


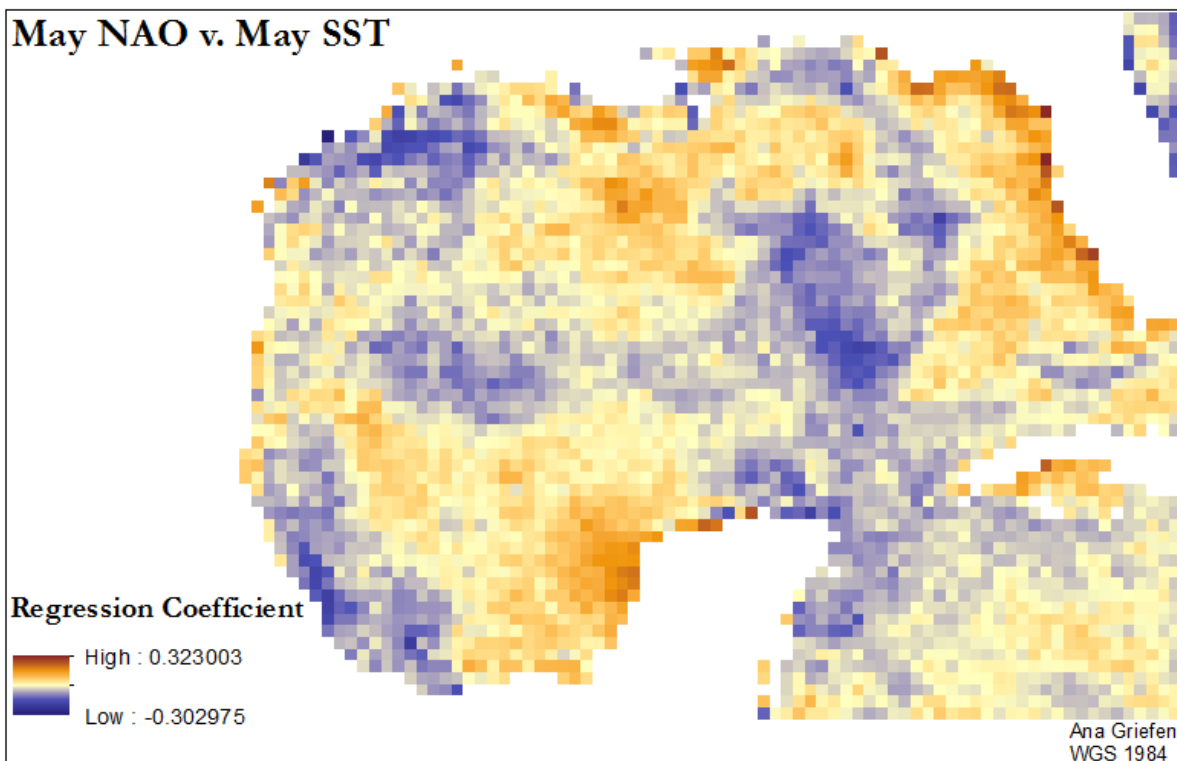
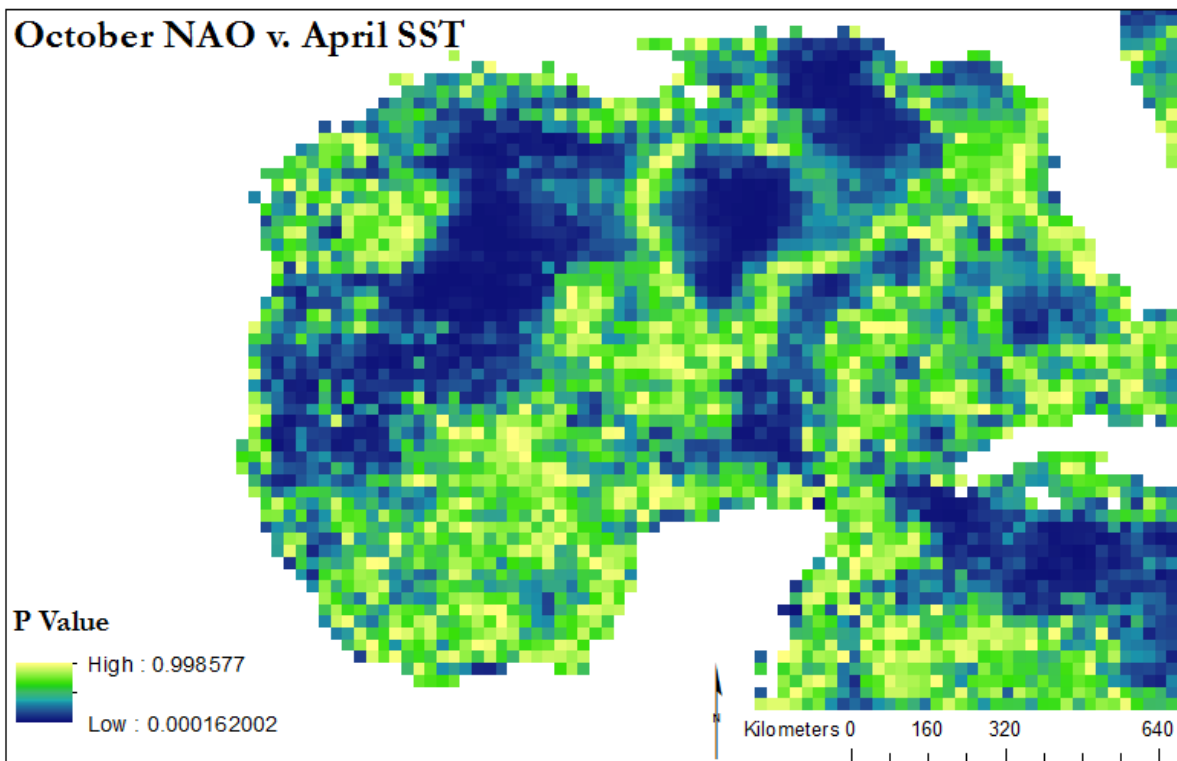




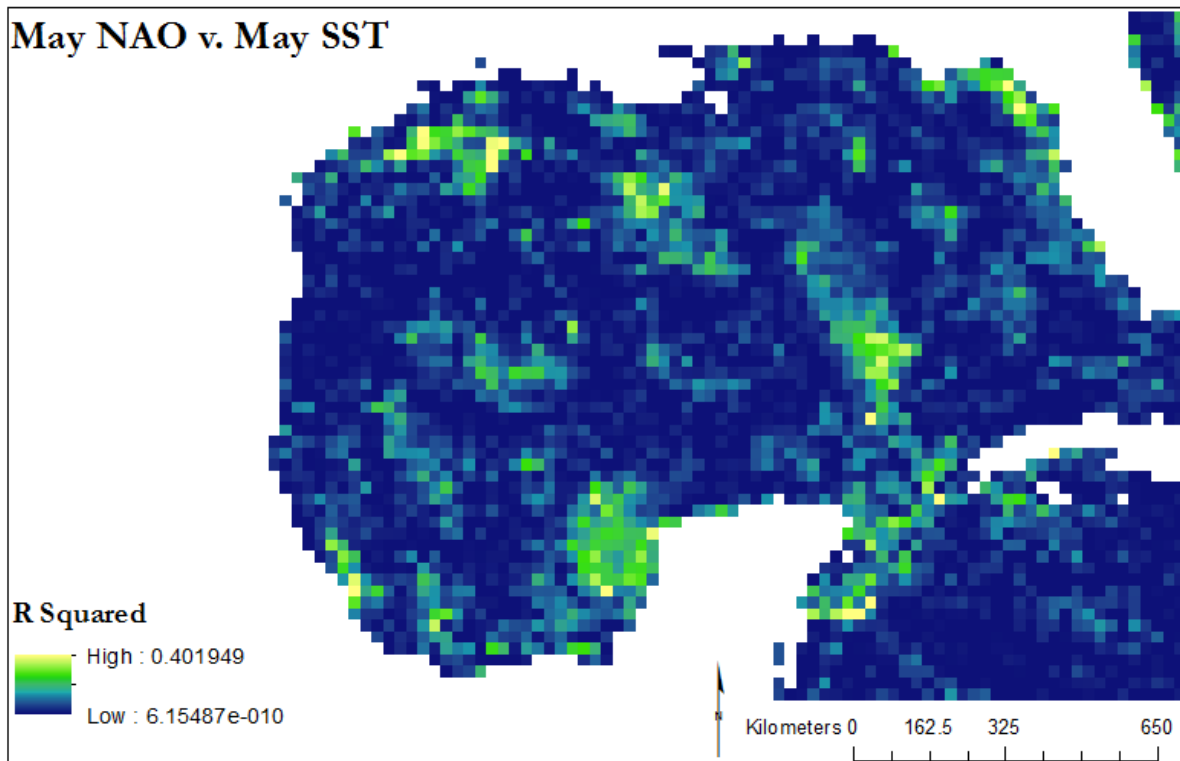




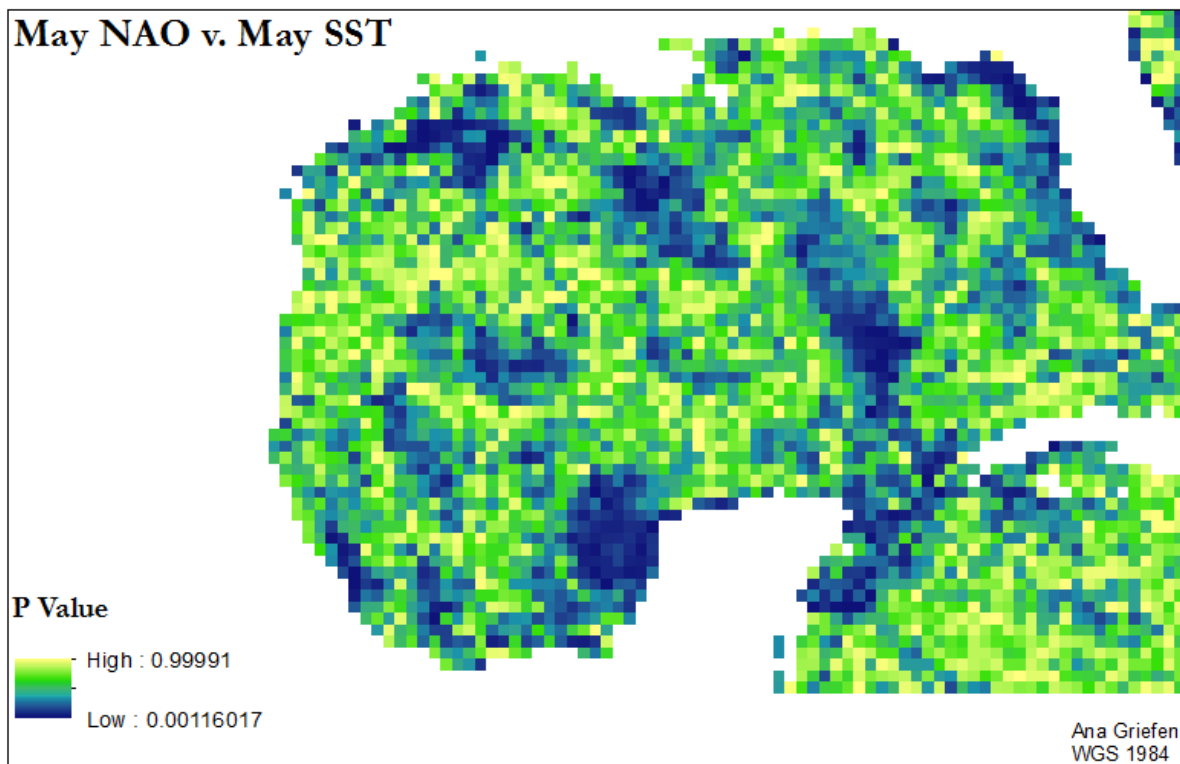




May NAO v. May SST

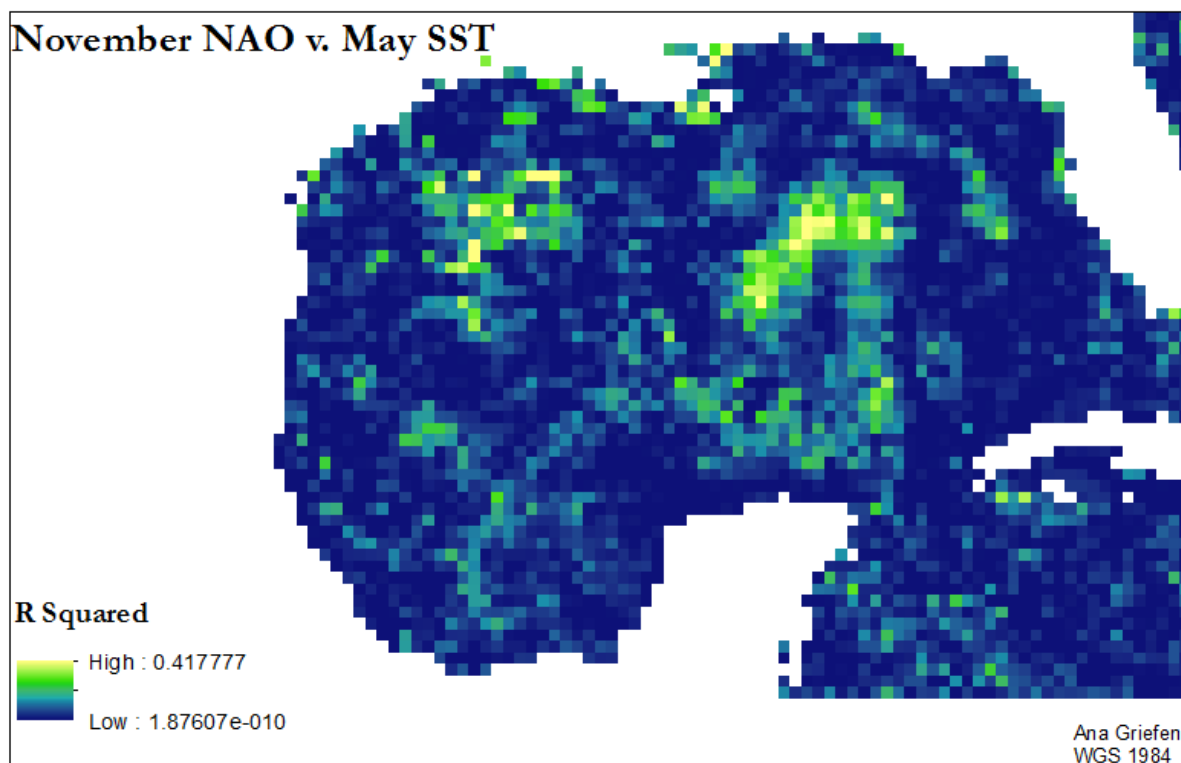
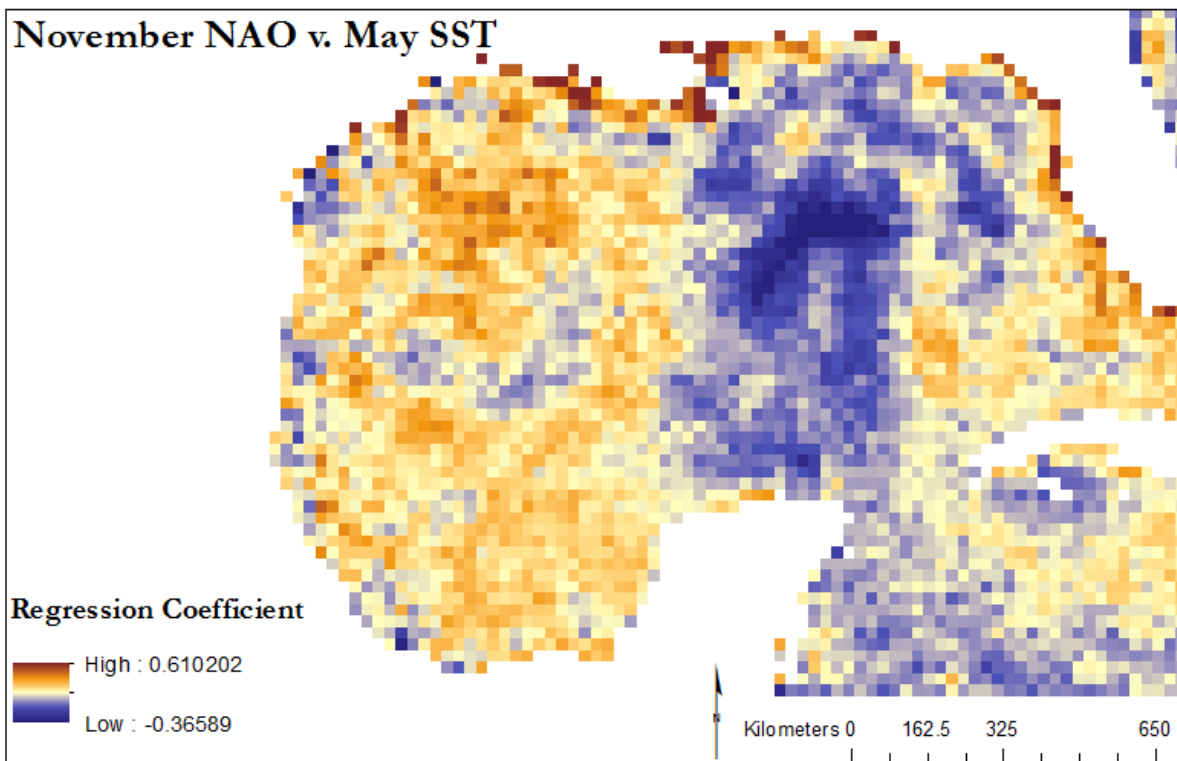


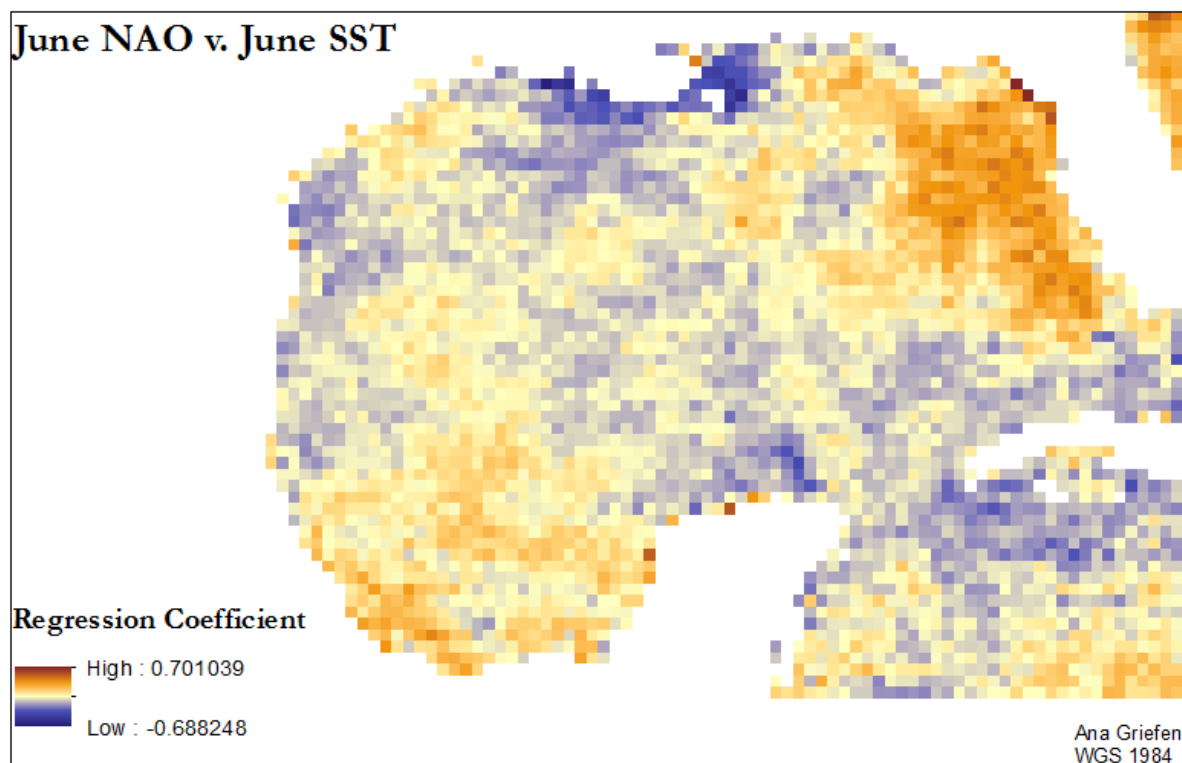
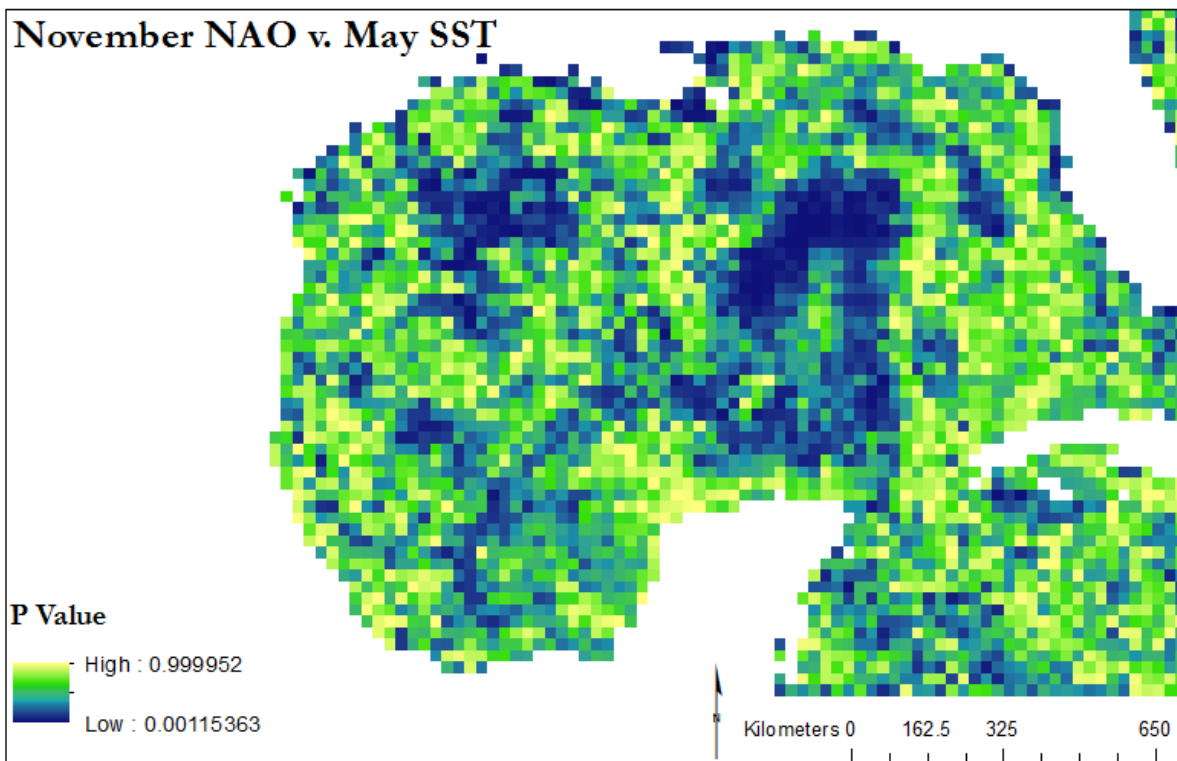
May NAO v. May SST

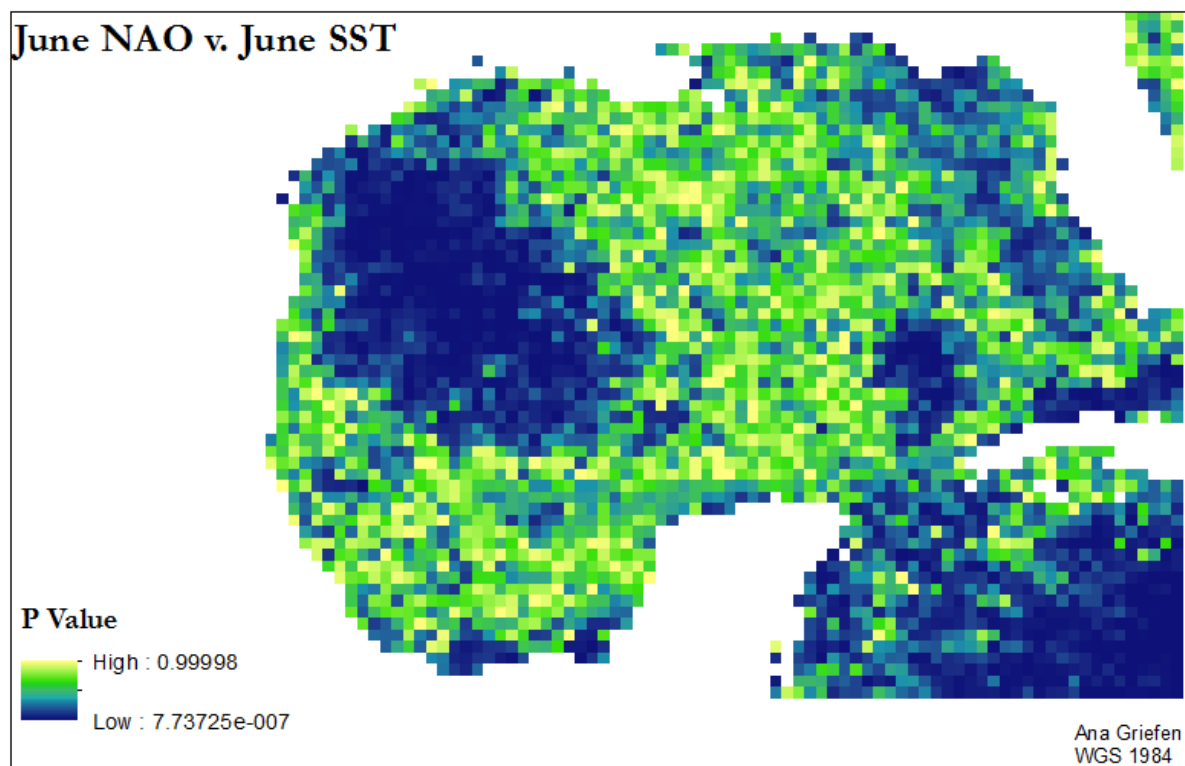
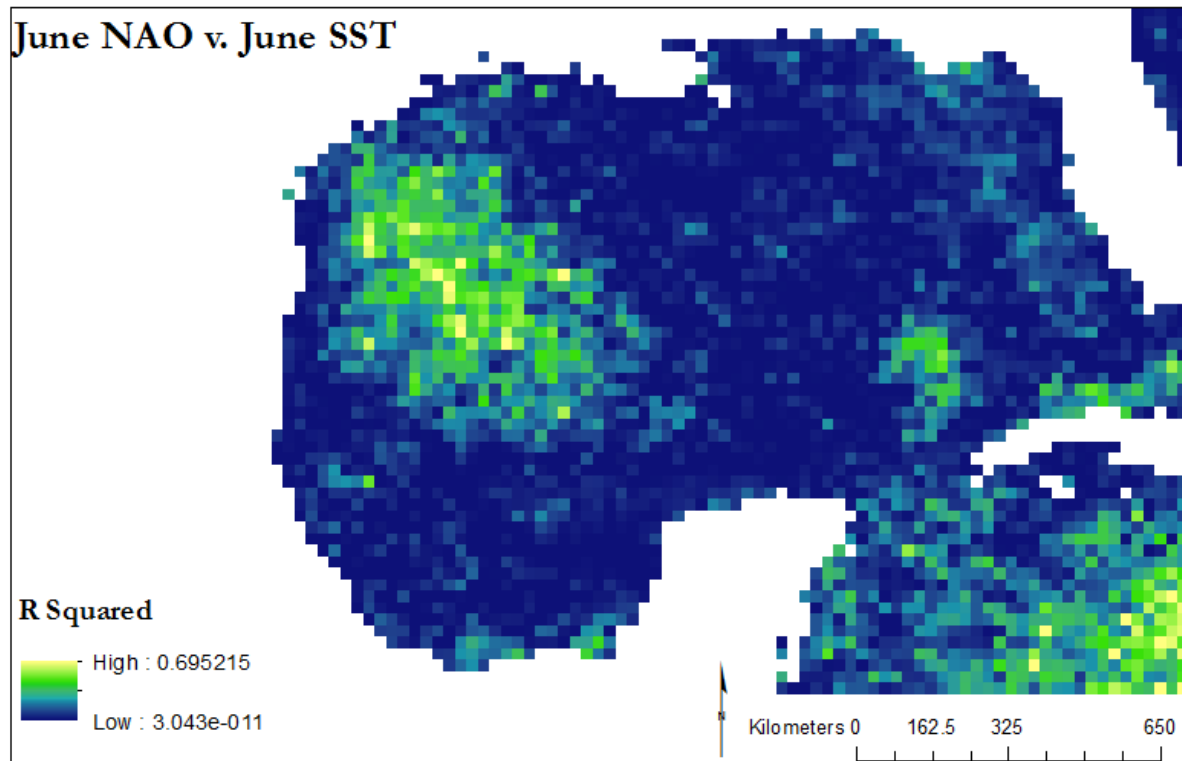


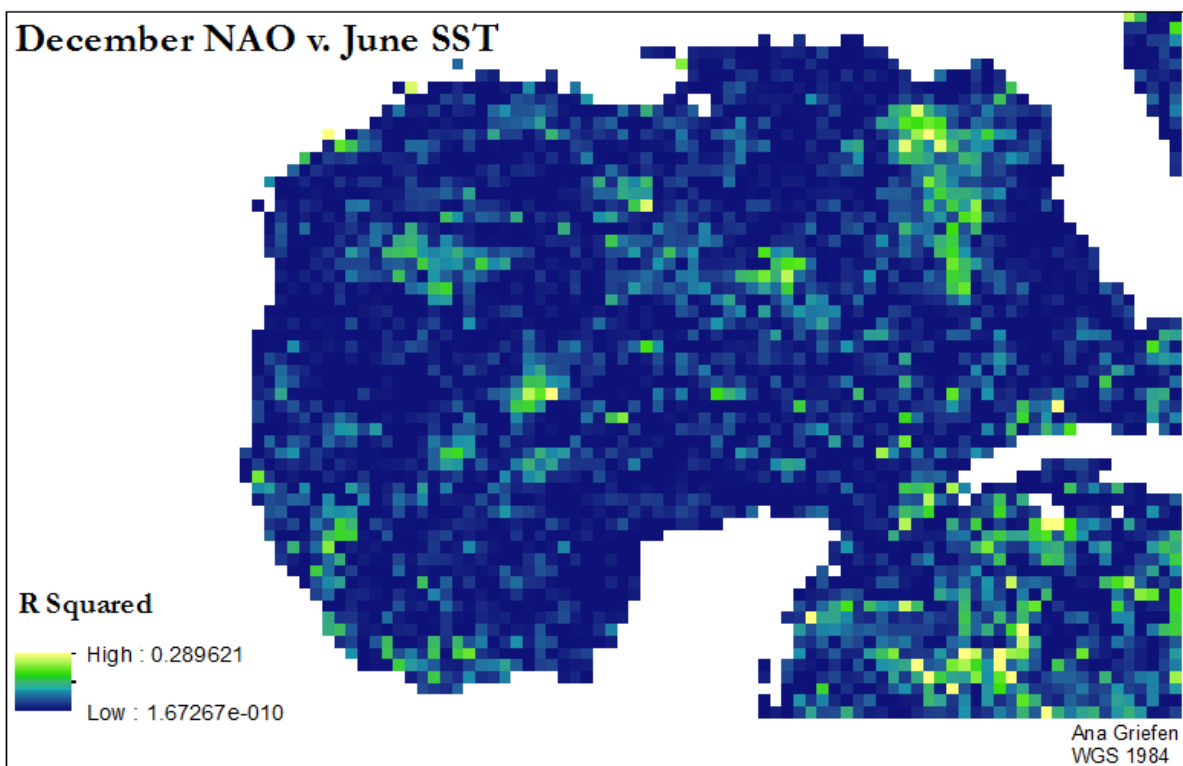
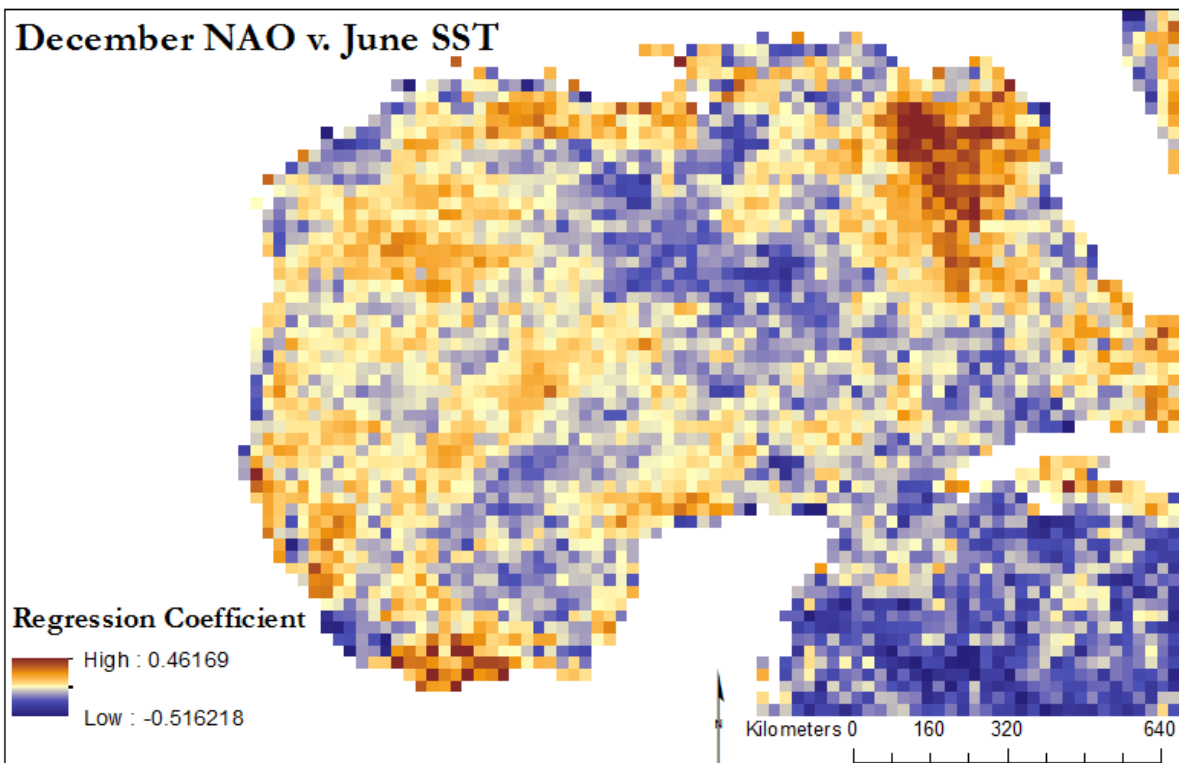
Ana Griefen  
WGS 1984

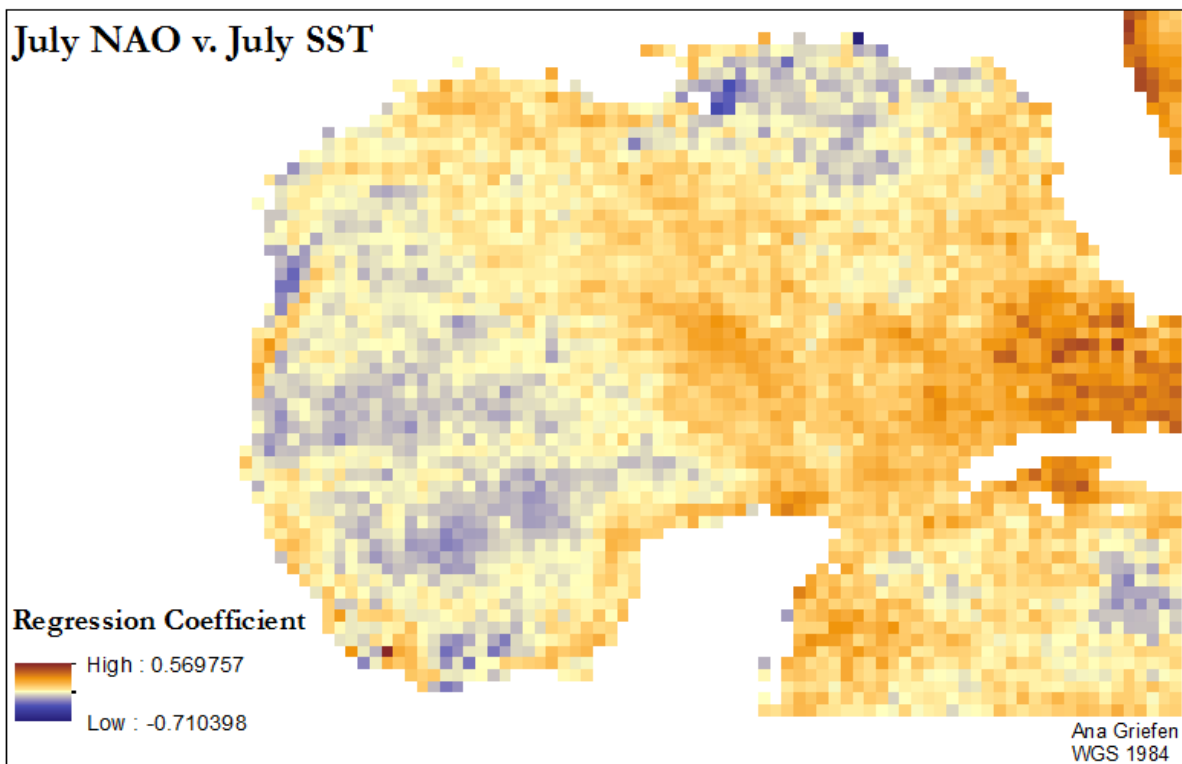
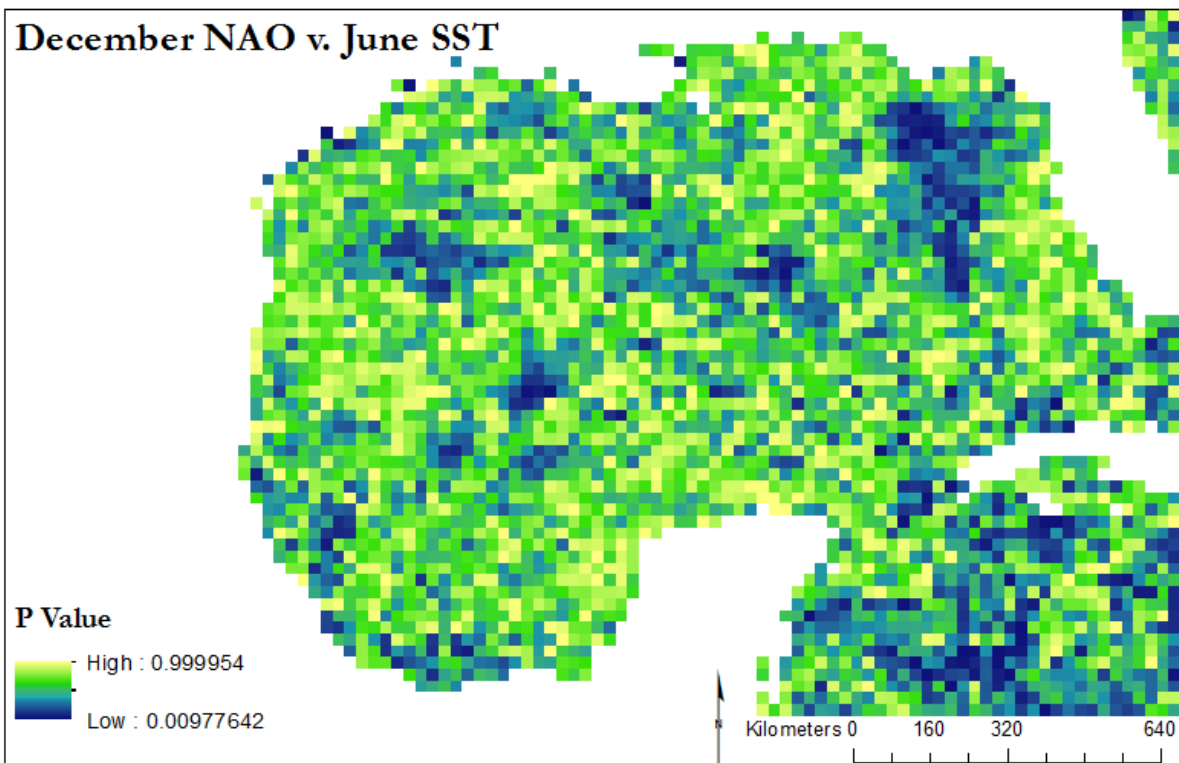


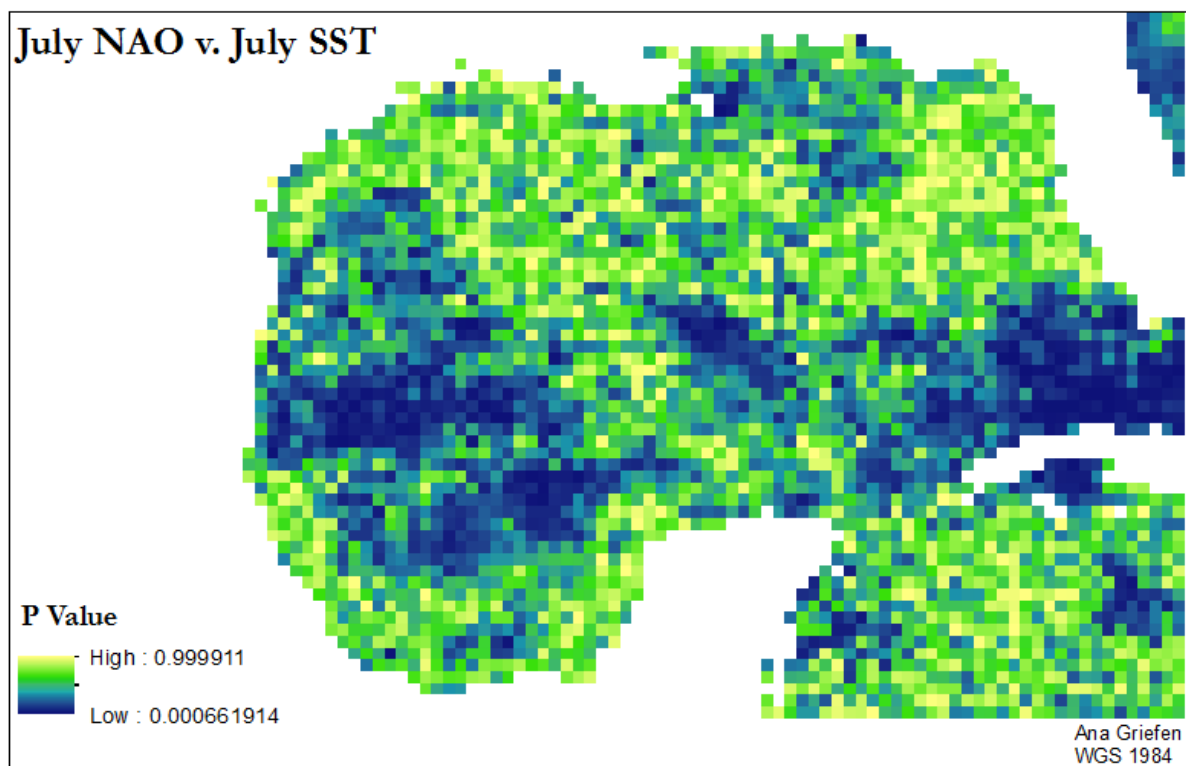
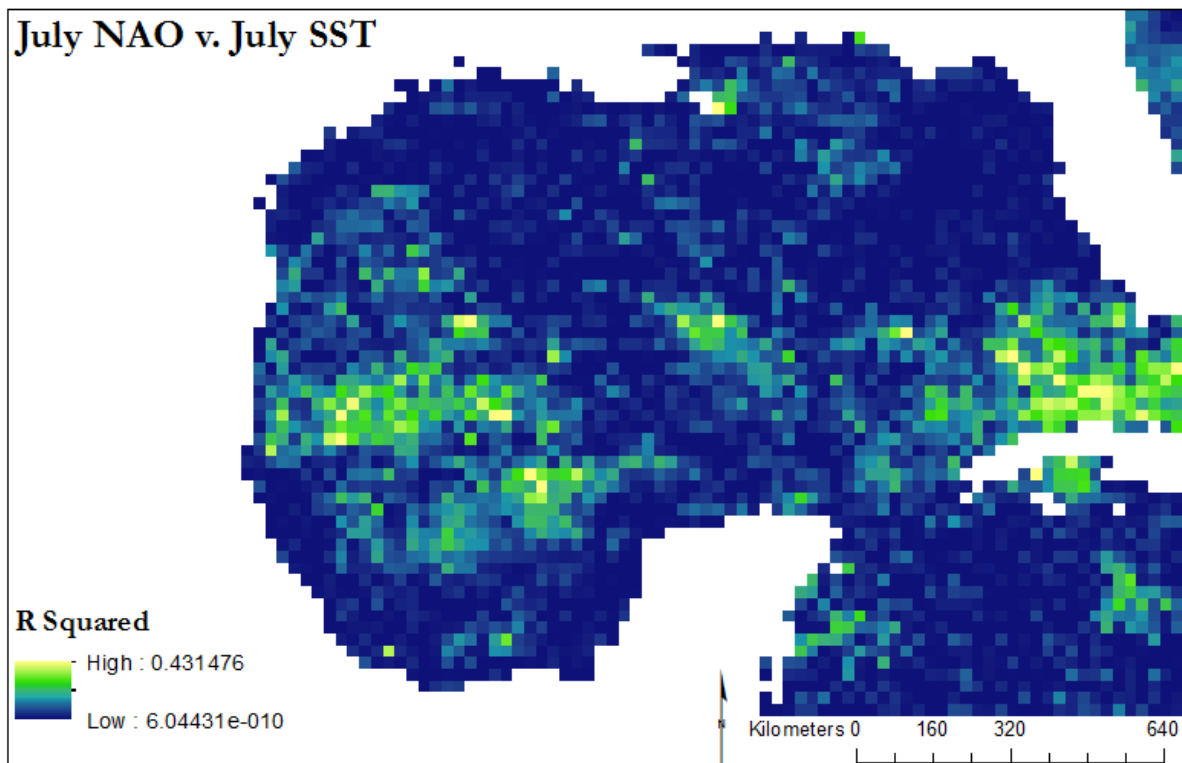


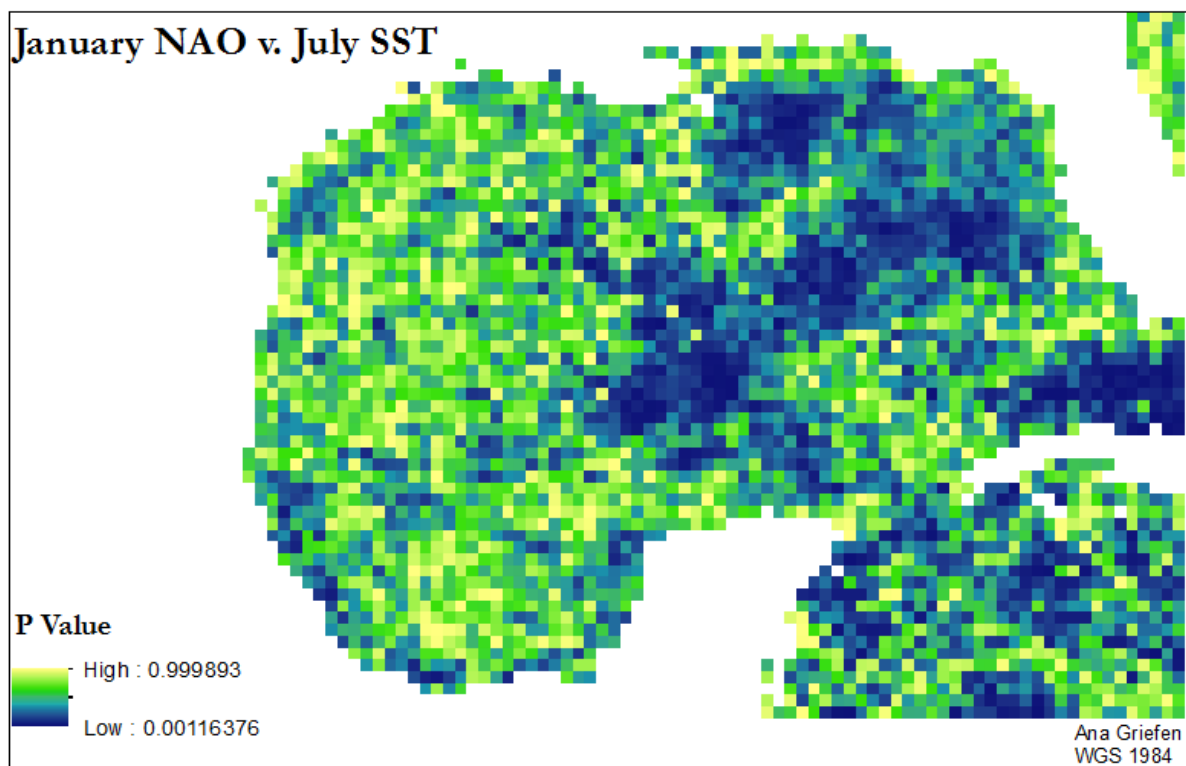
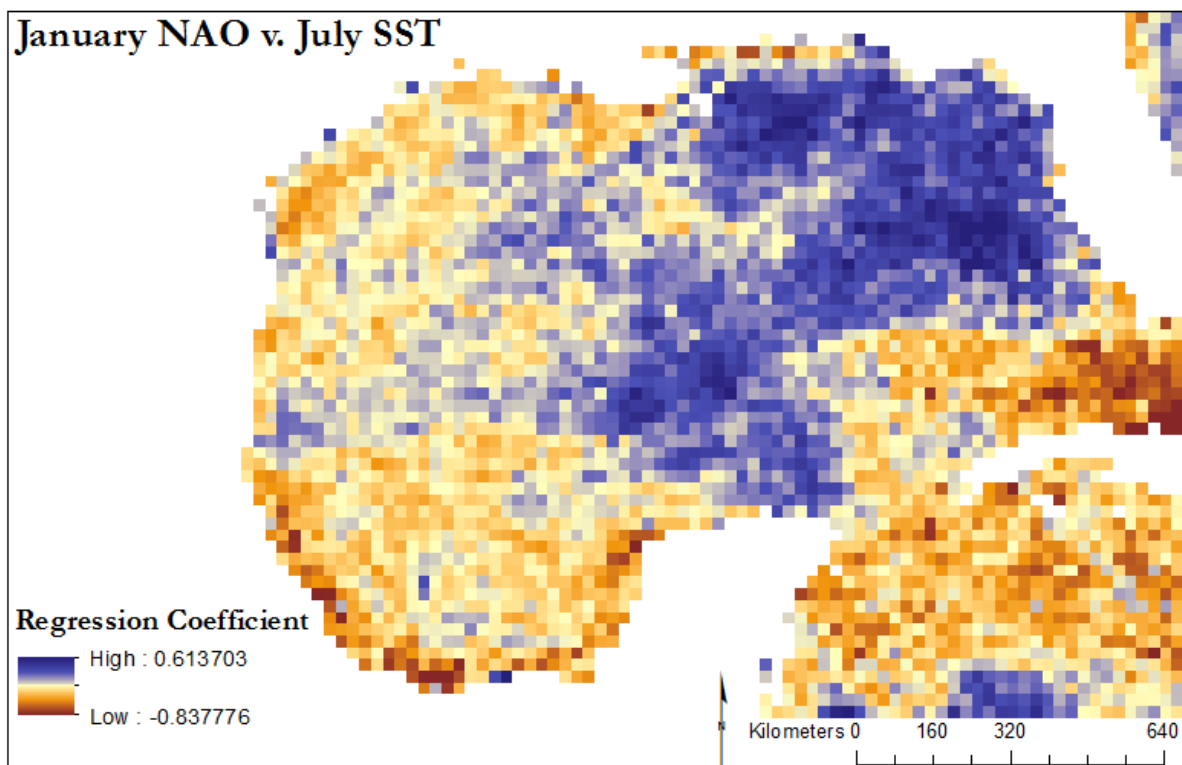




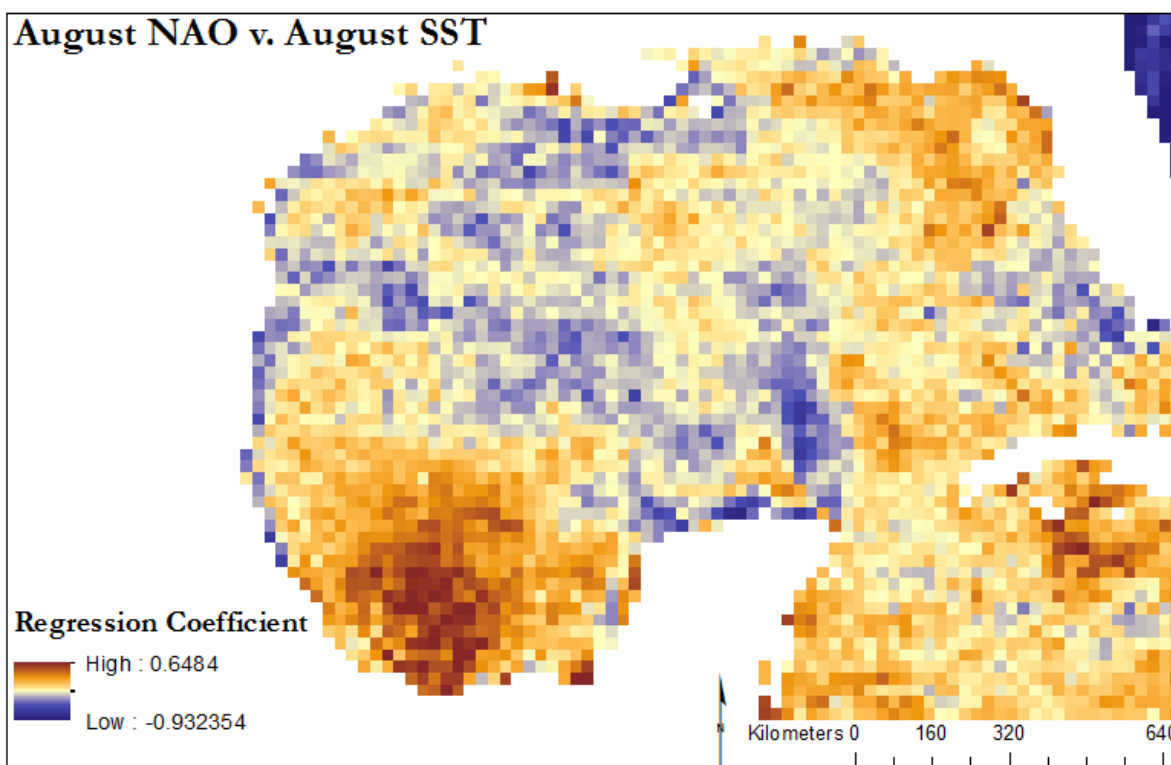




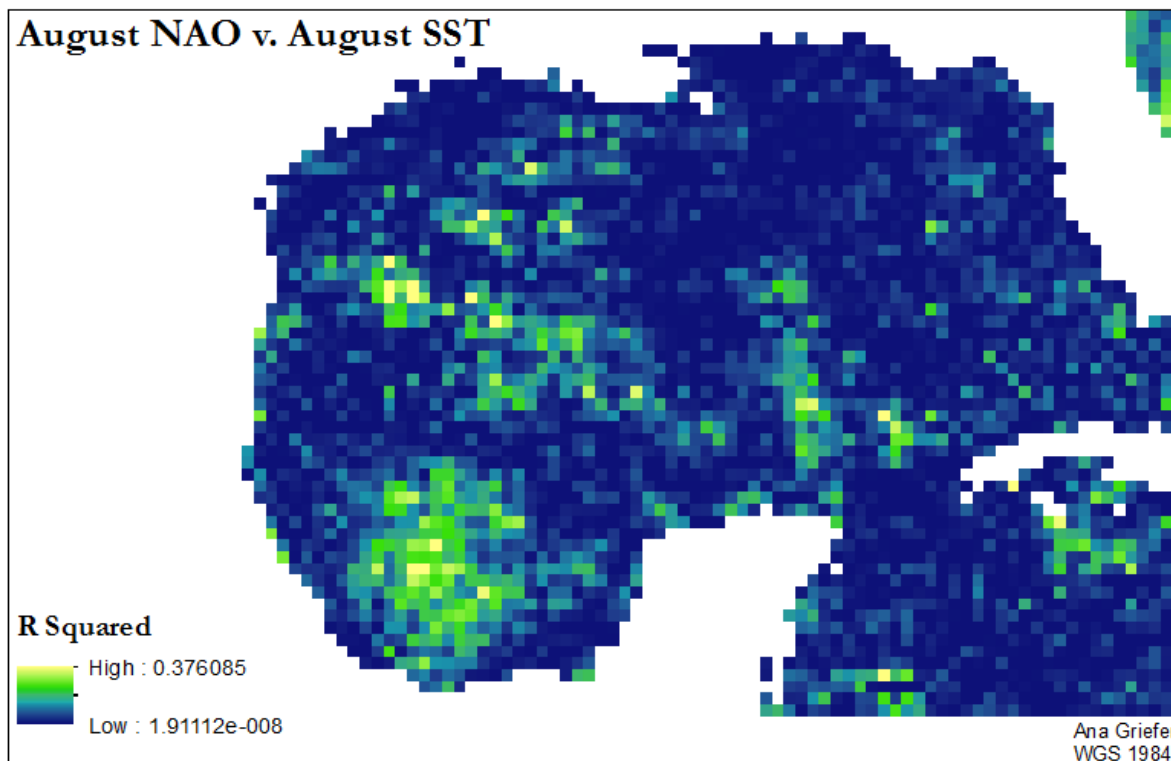




August NAO v. August SST

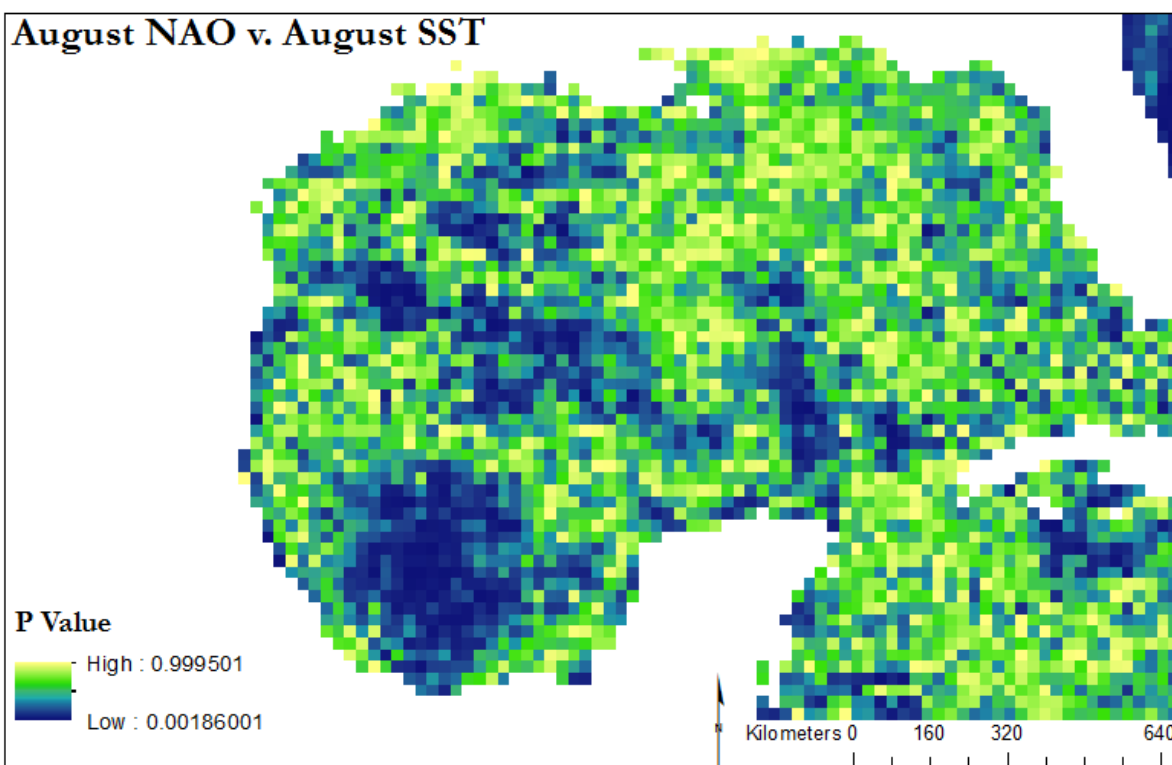


August NAO v. August SST

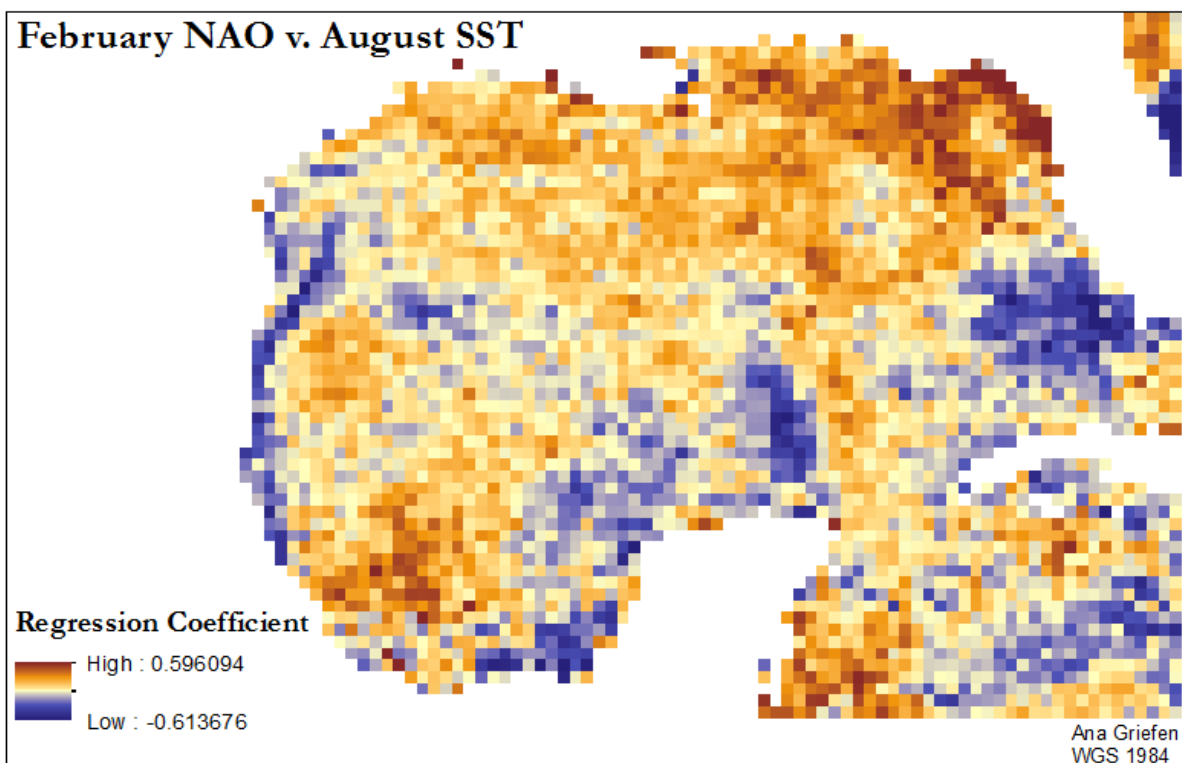


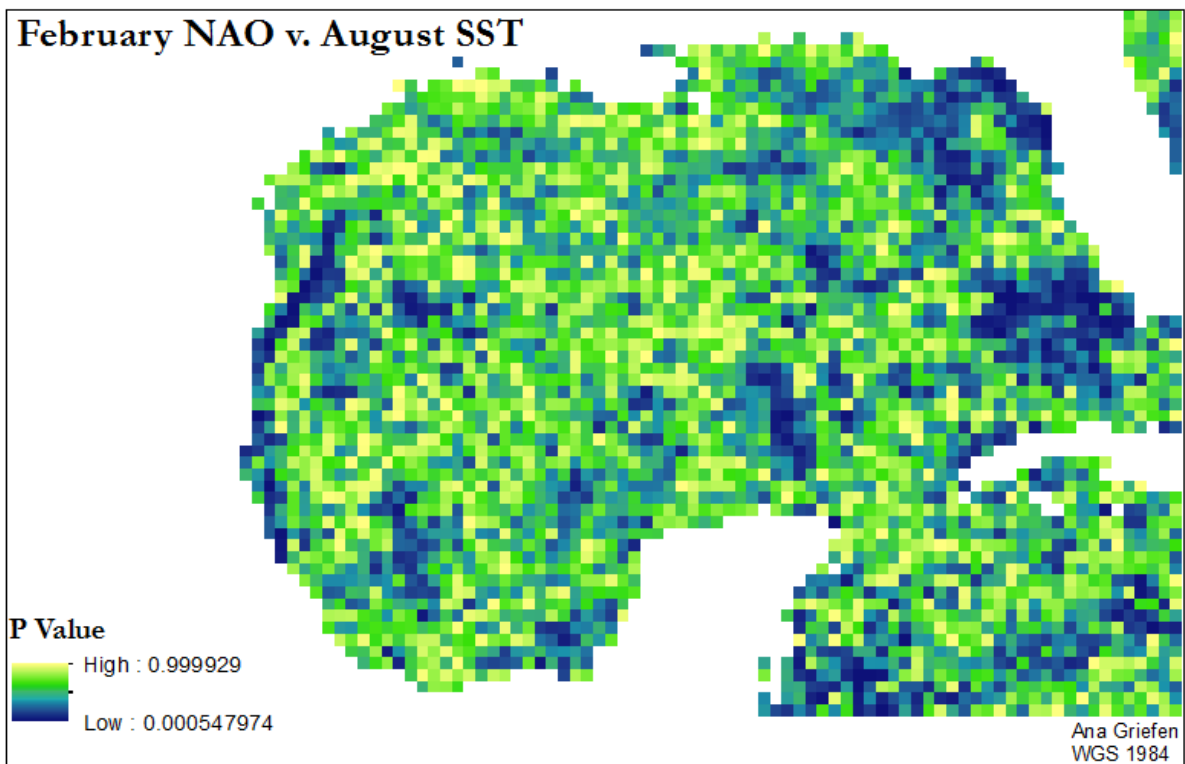
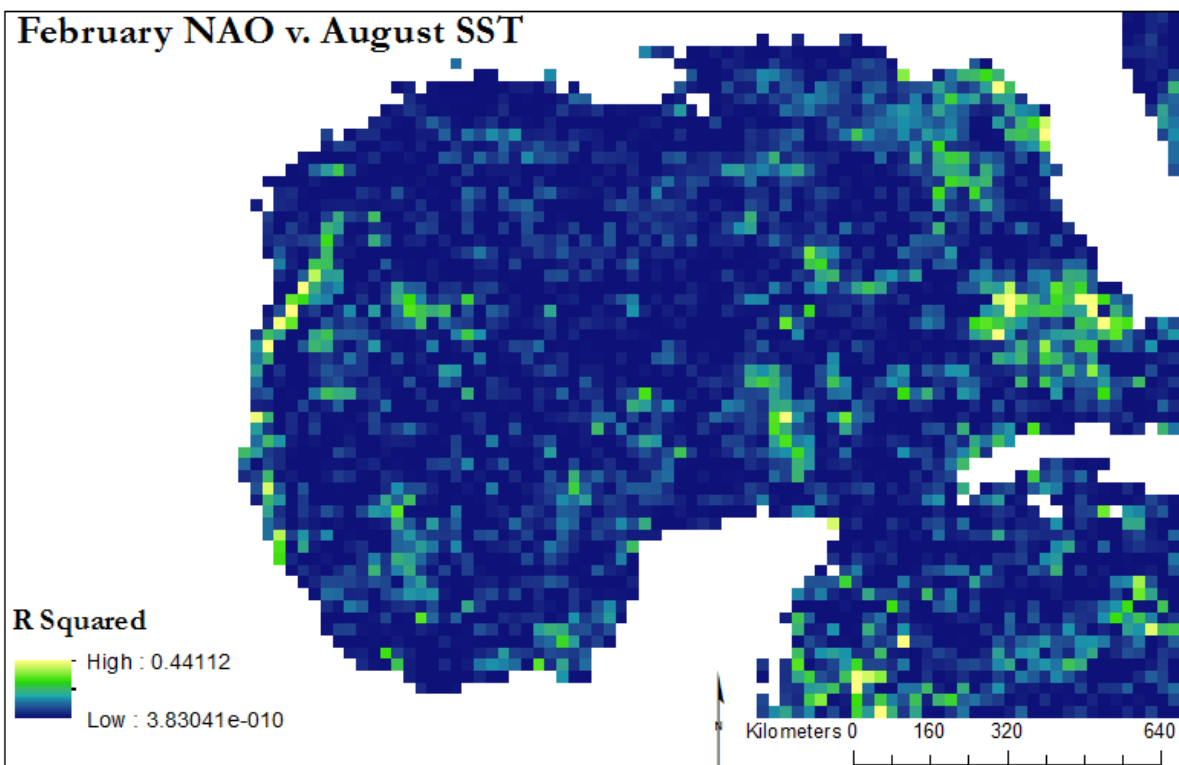


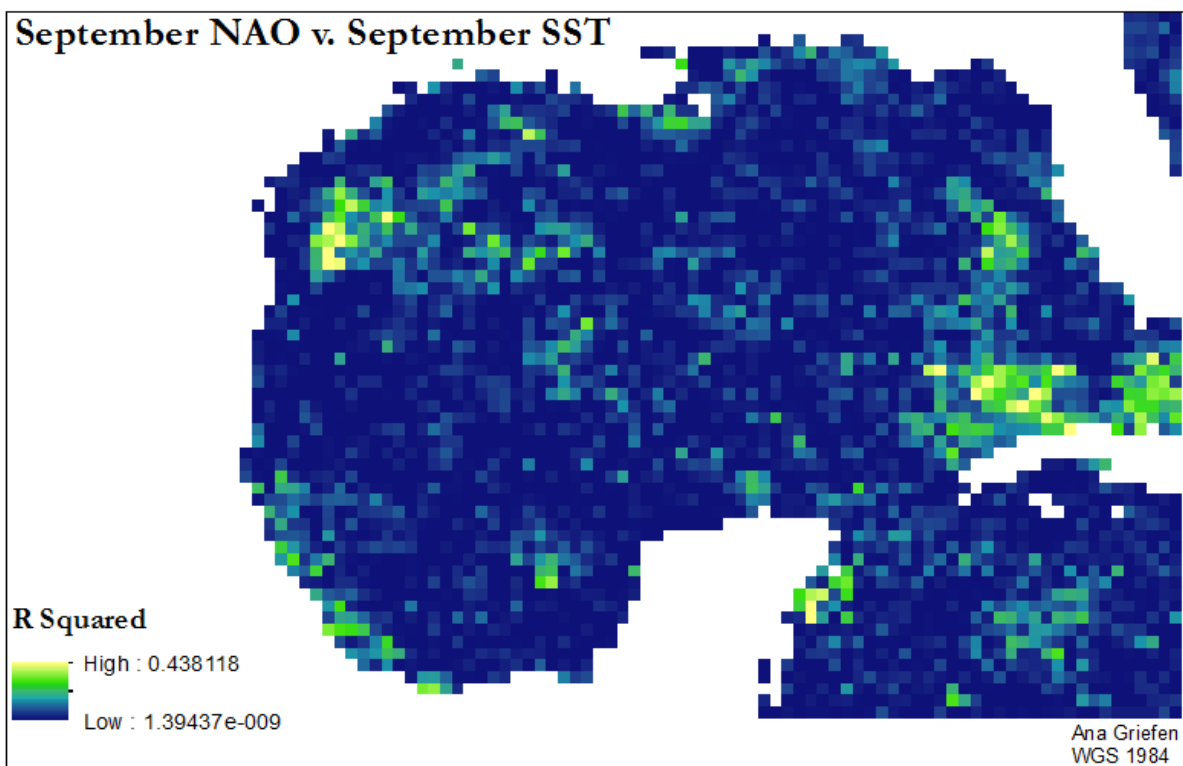
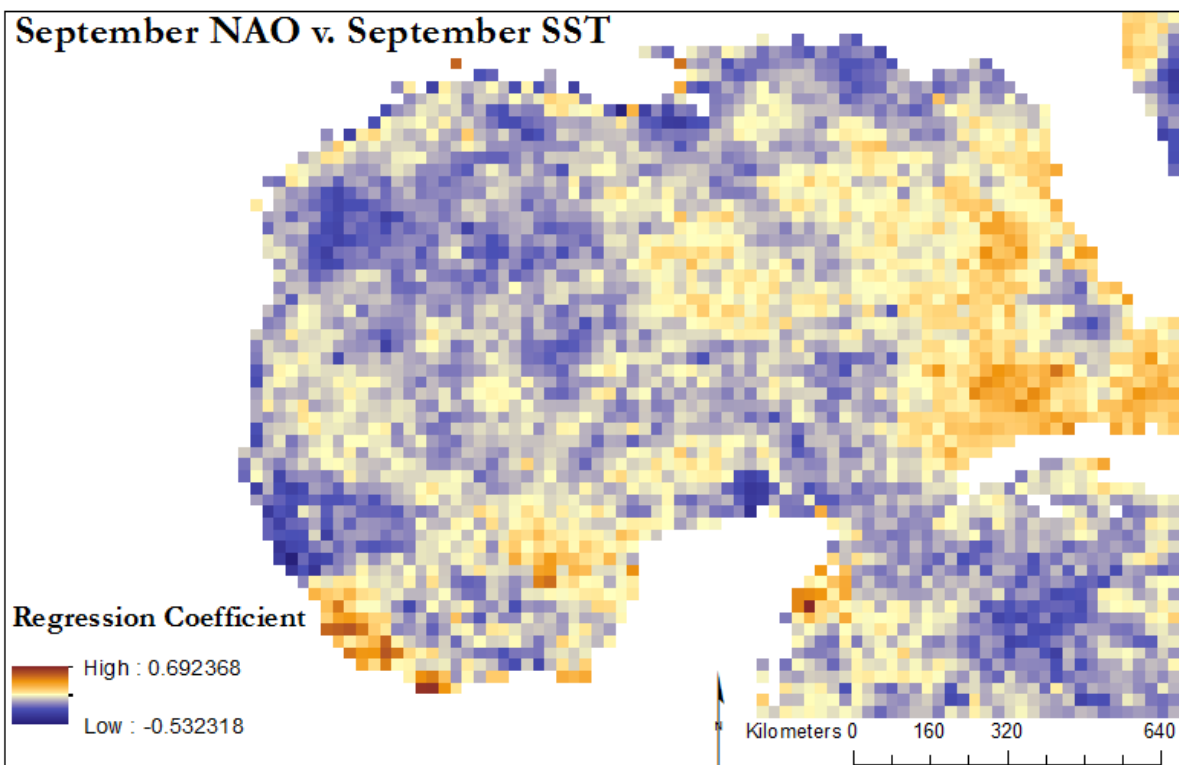
August NAO v. August SST

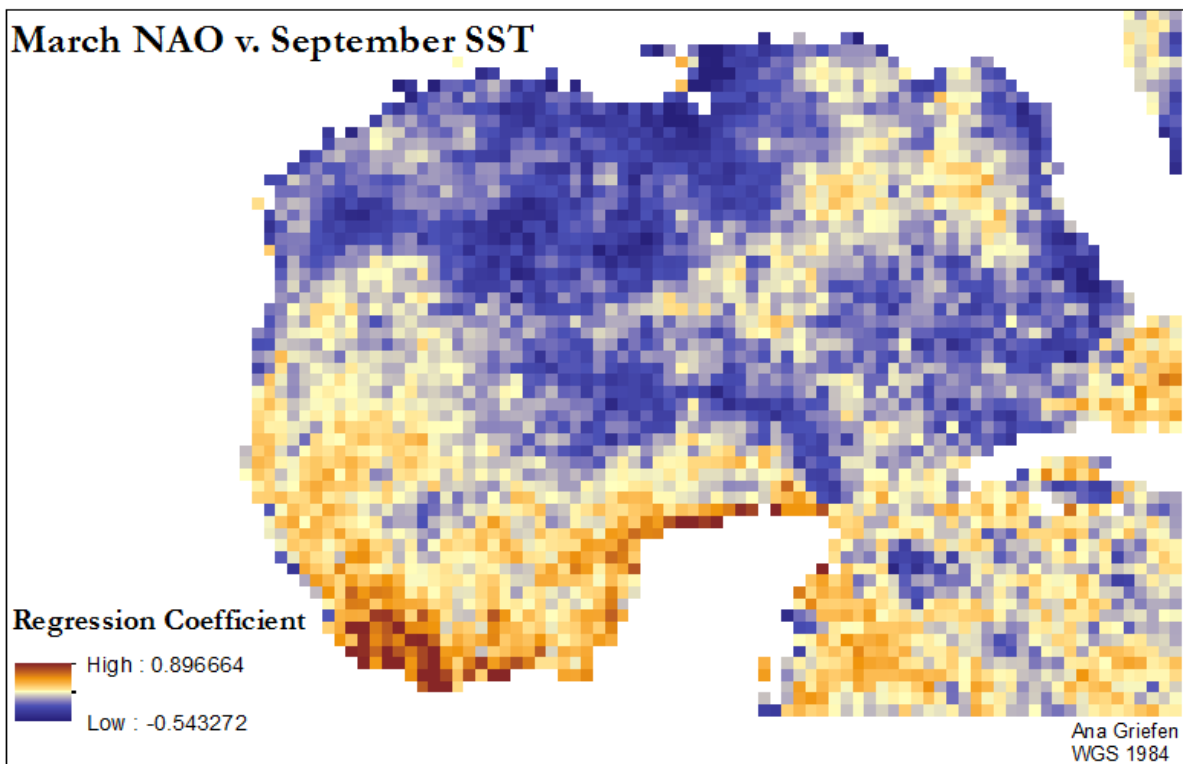
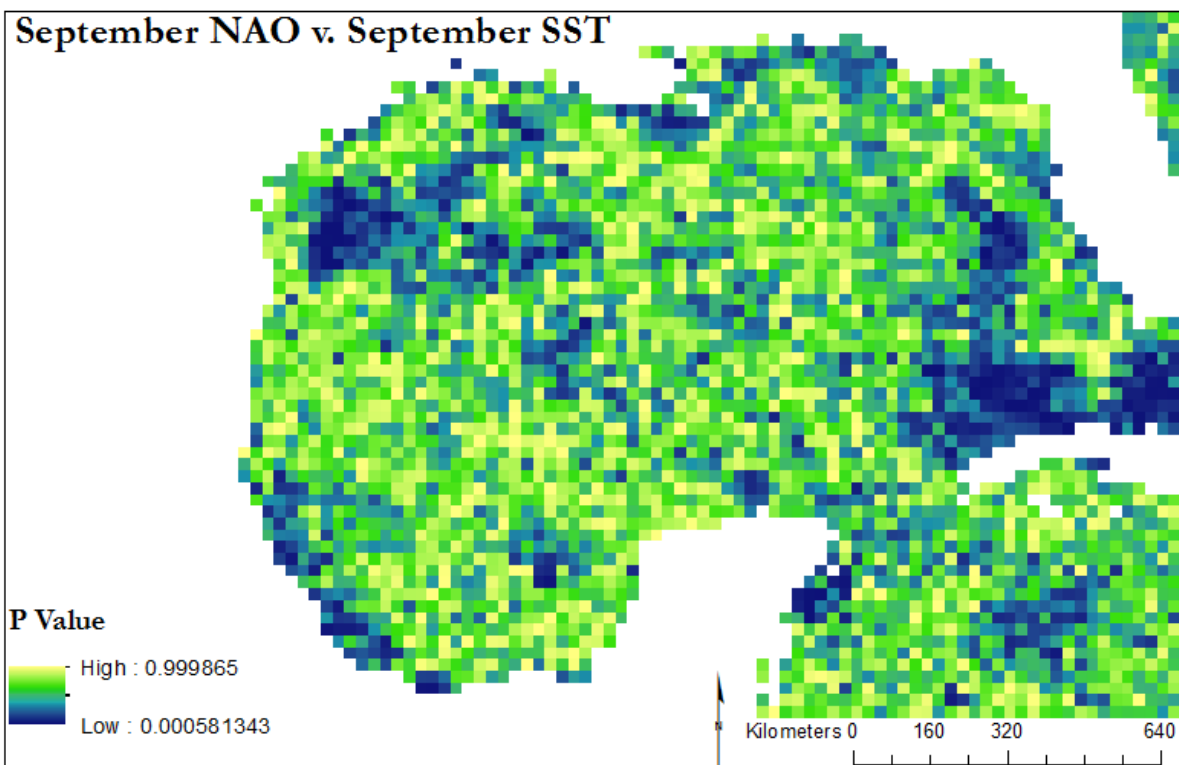


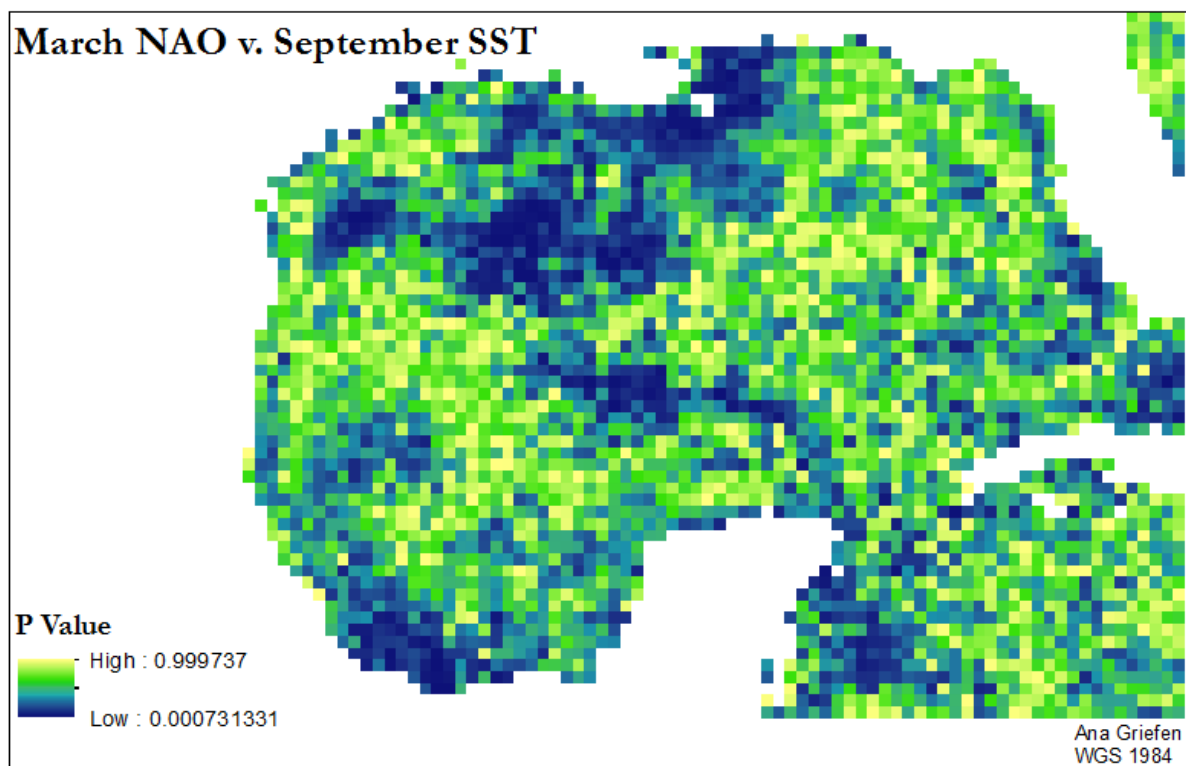
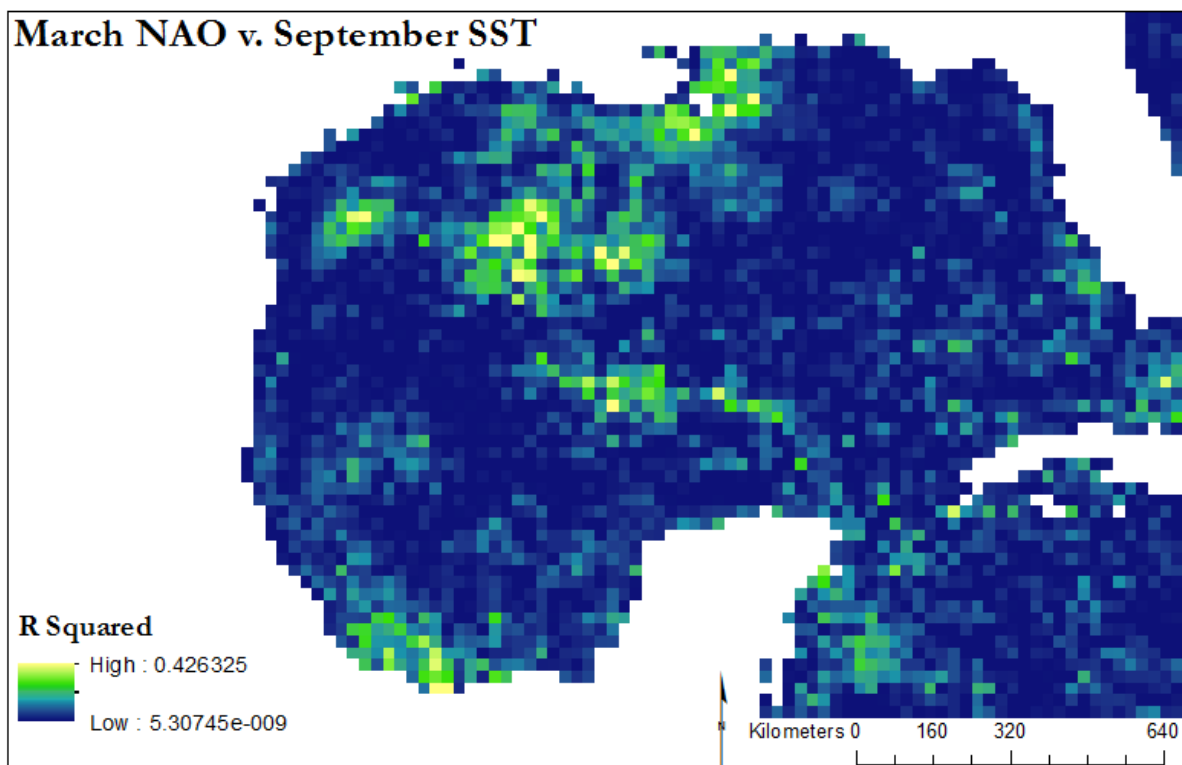
February NAO v. August SST

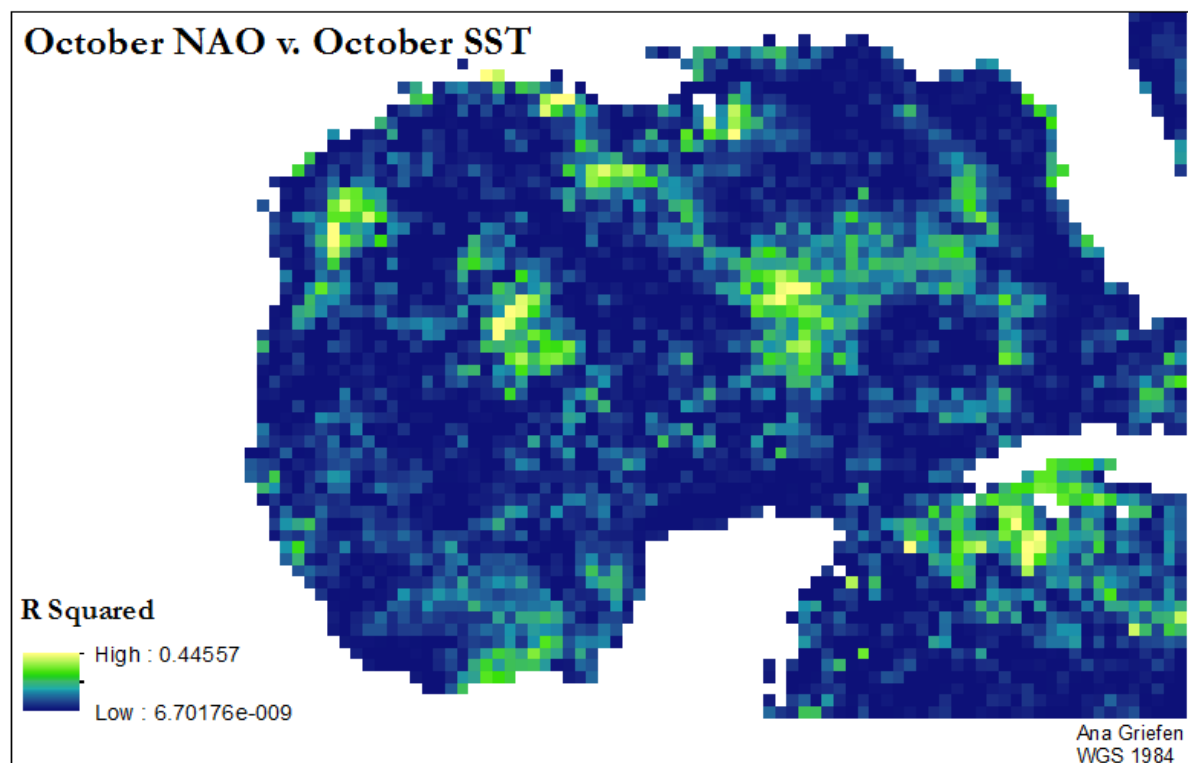
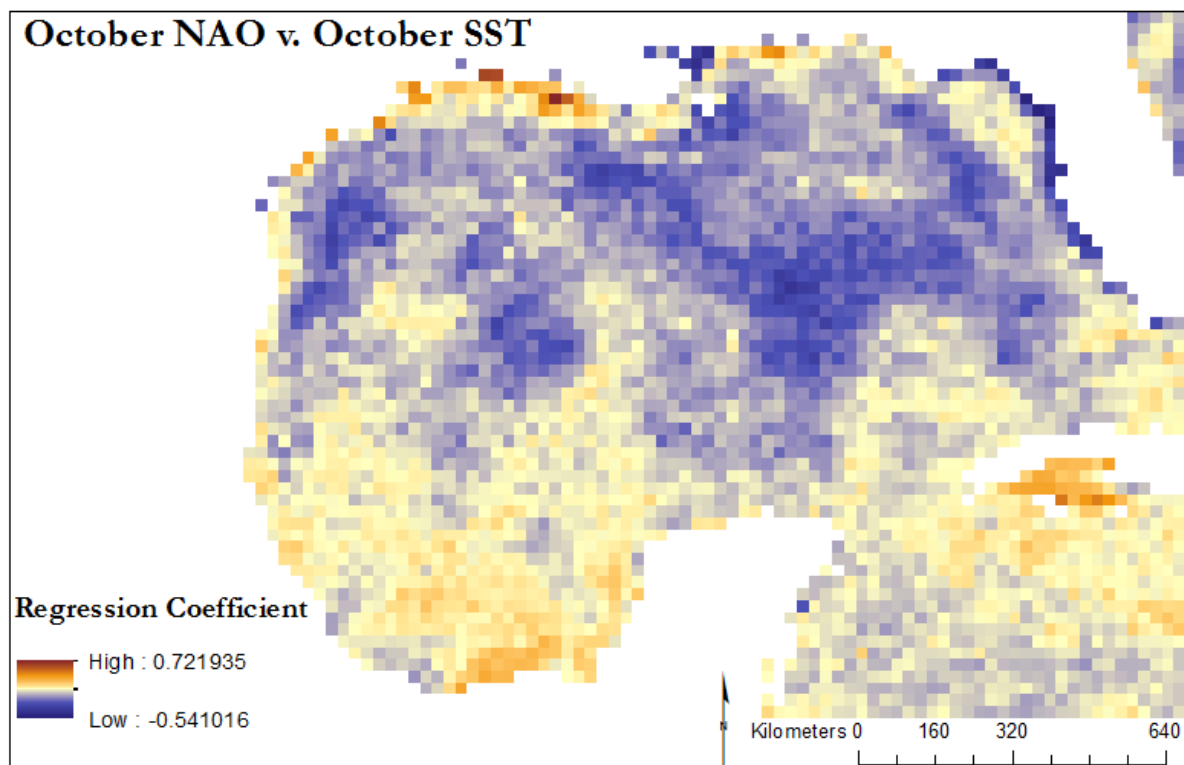


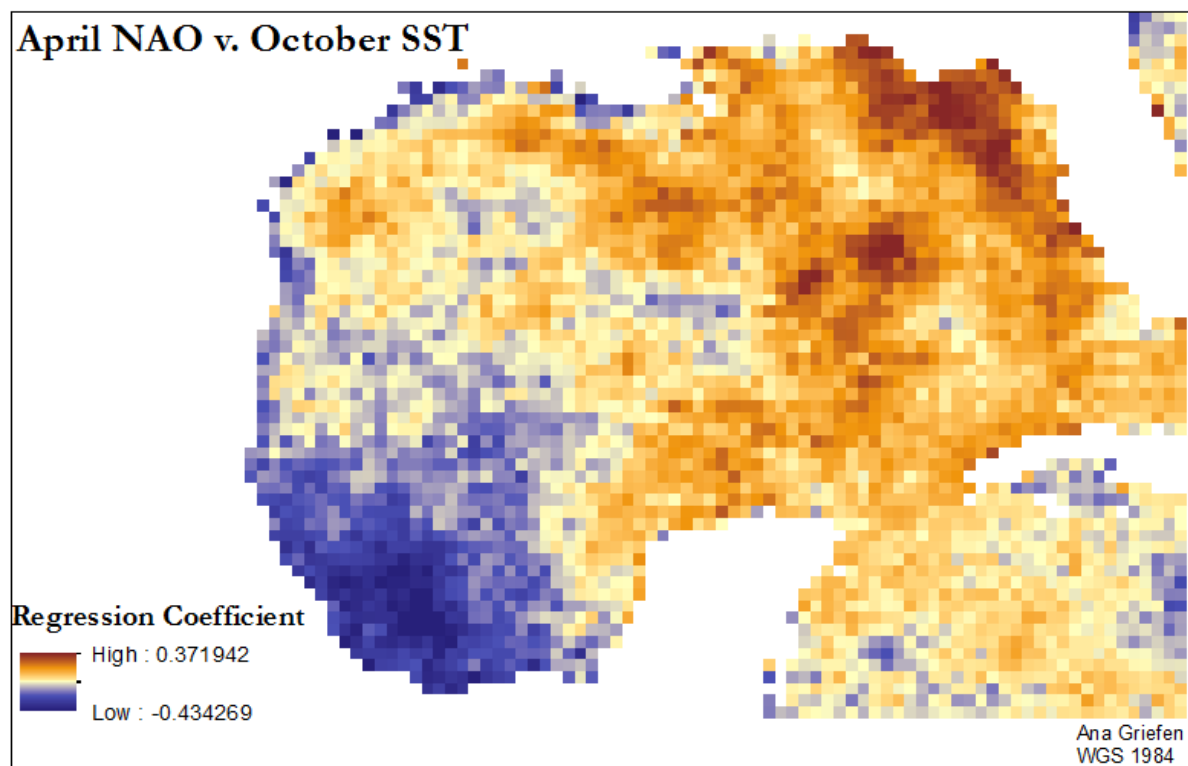
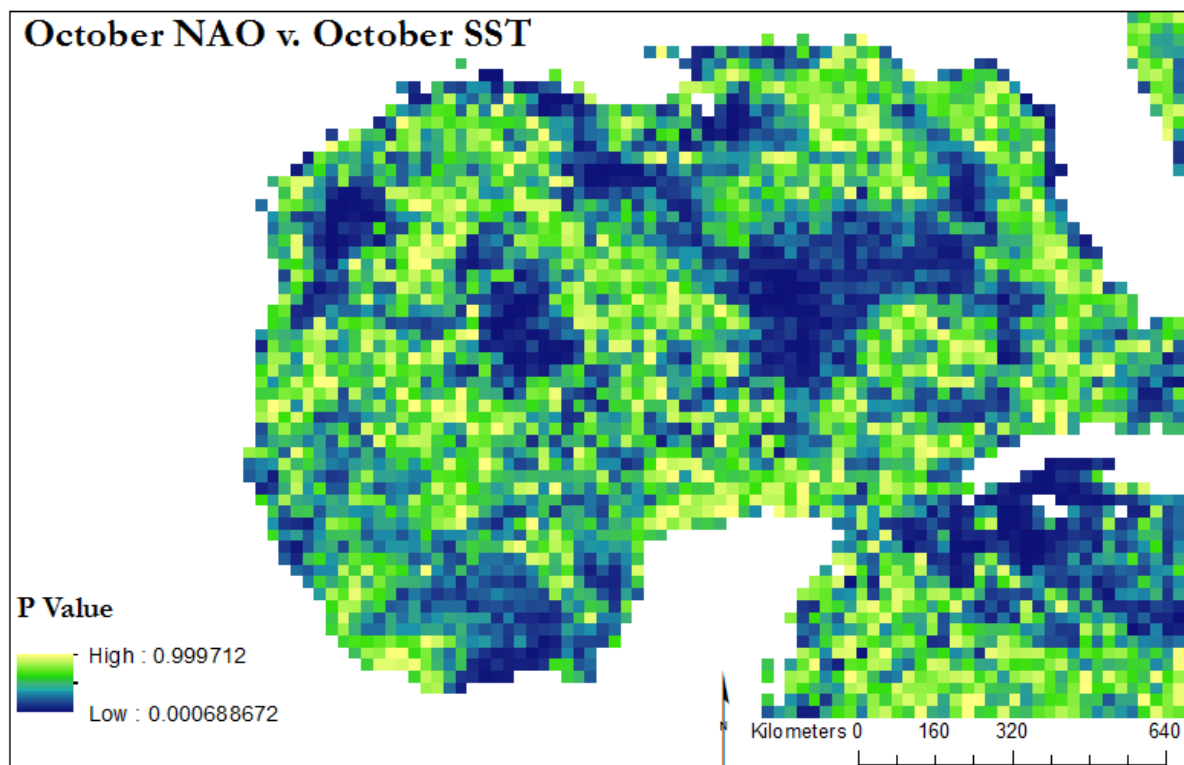


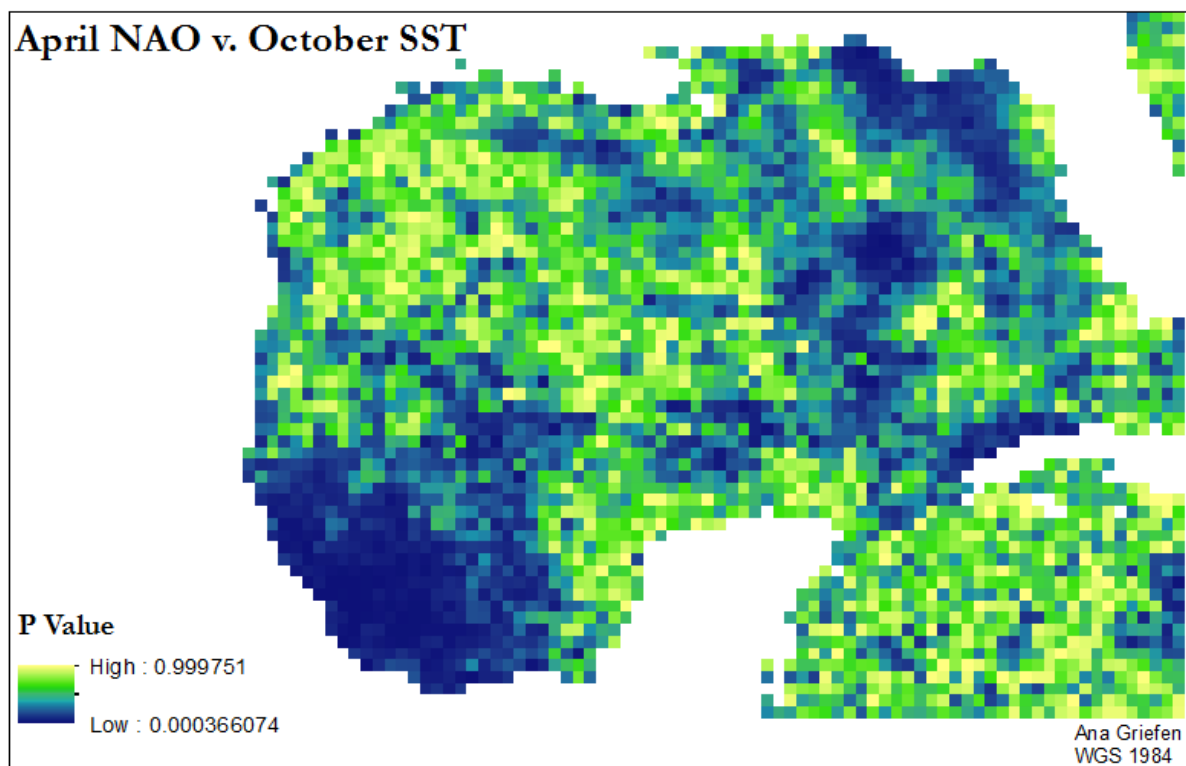
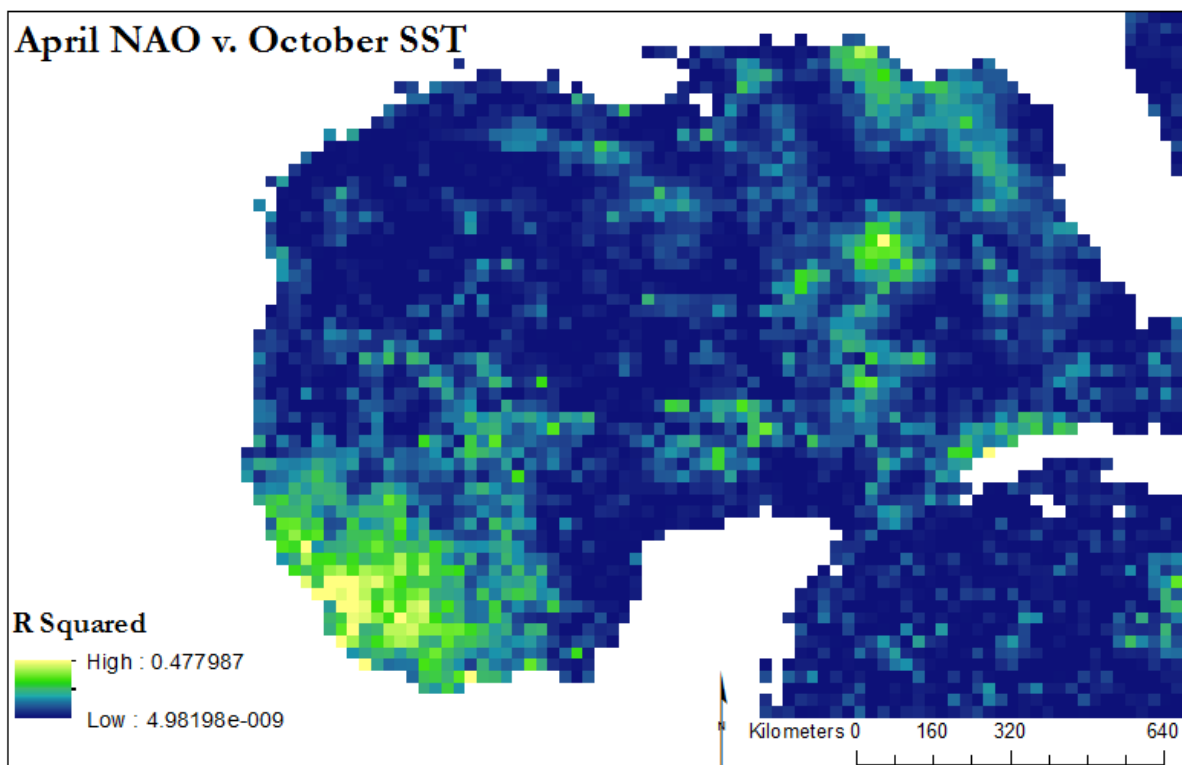




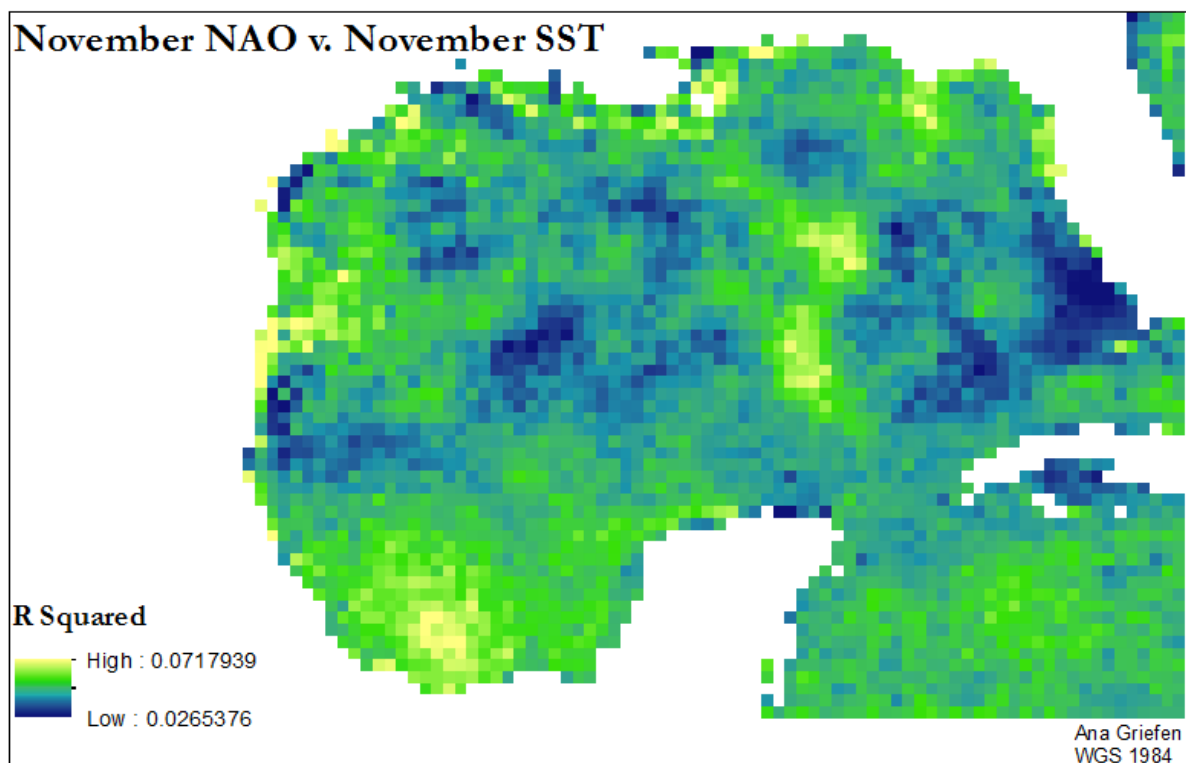
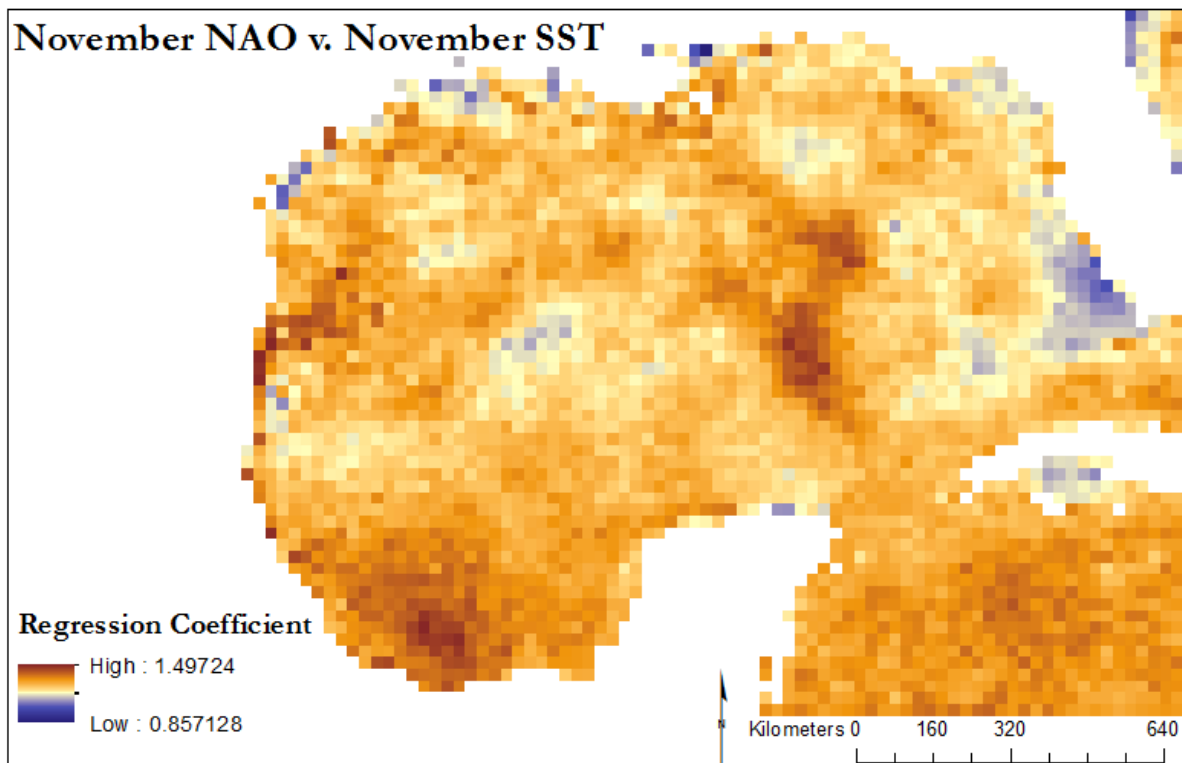


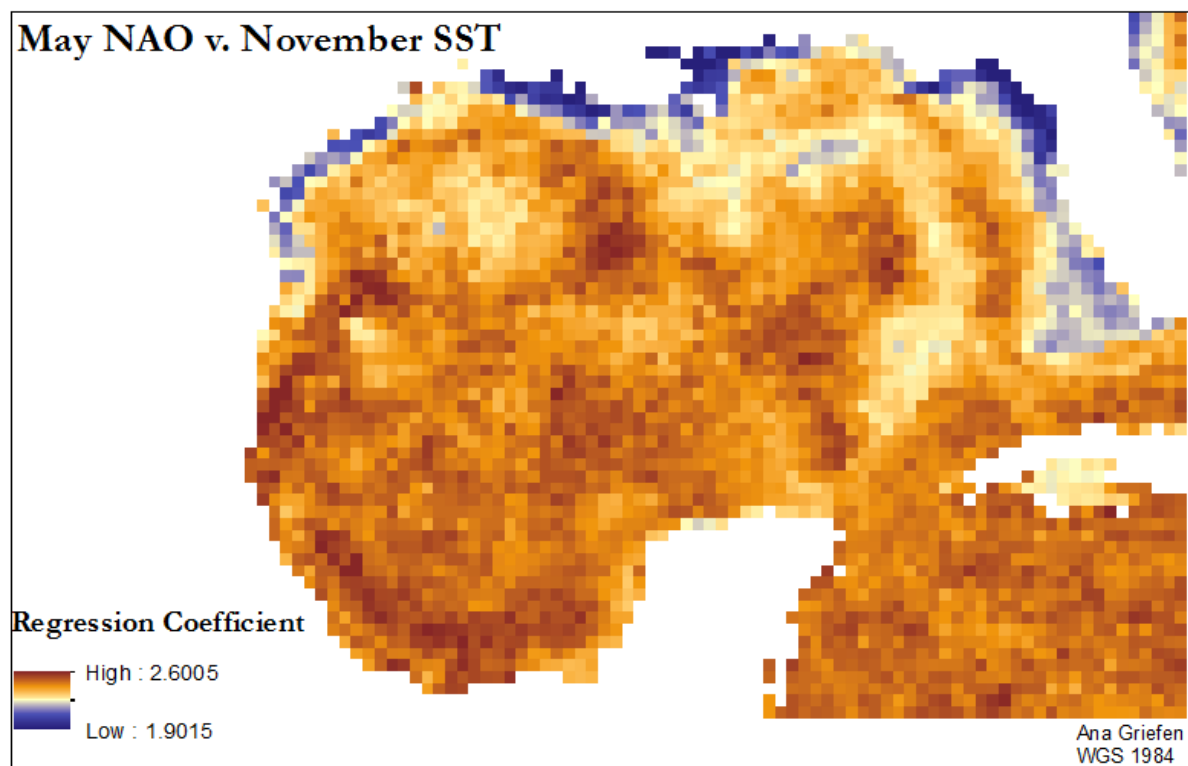
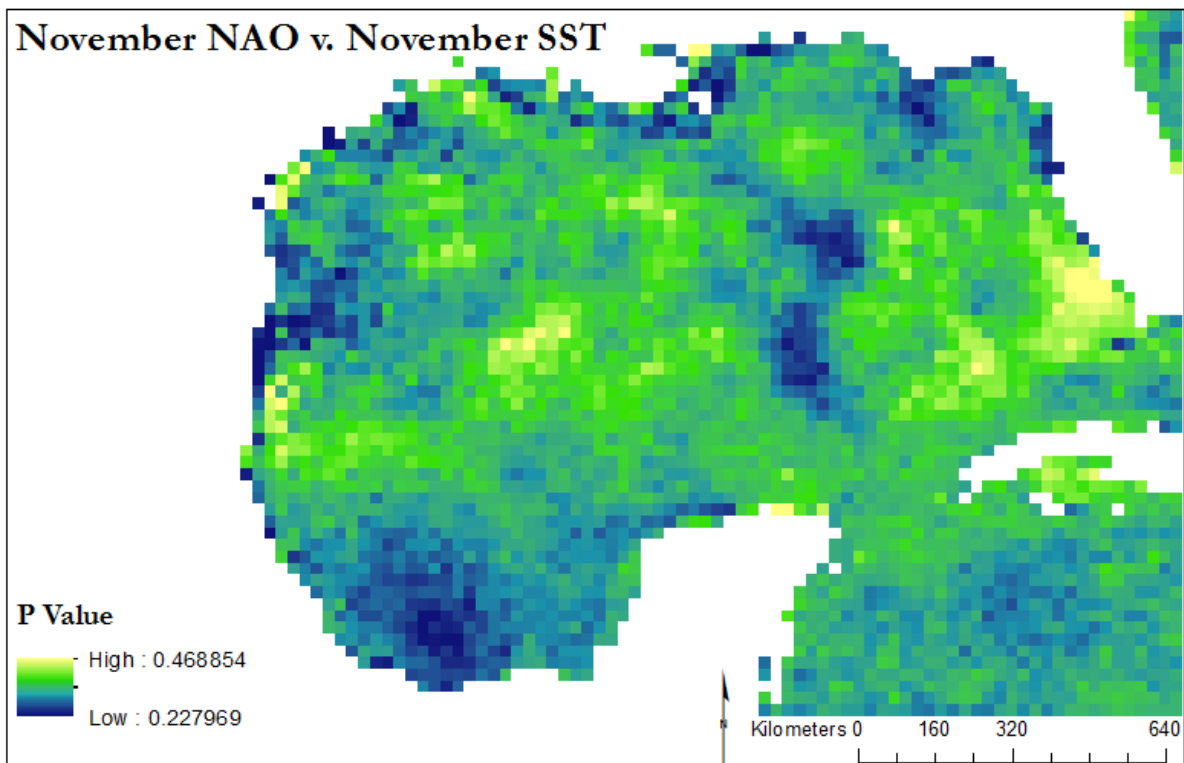


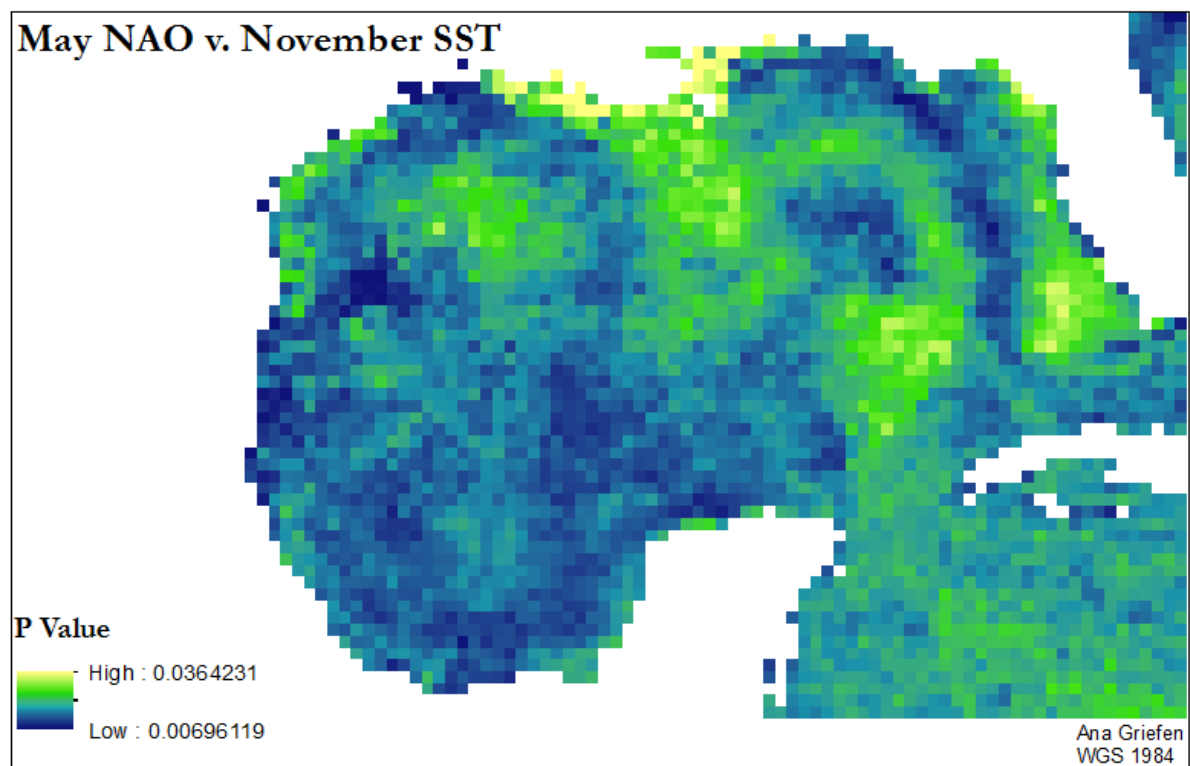
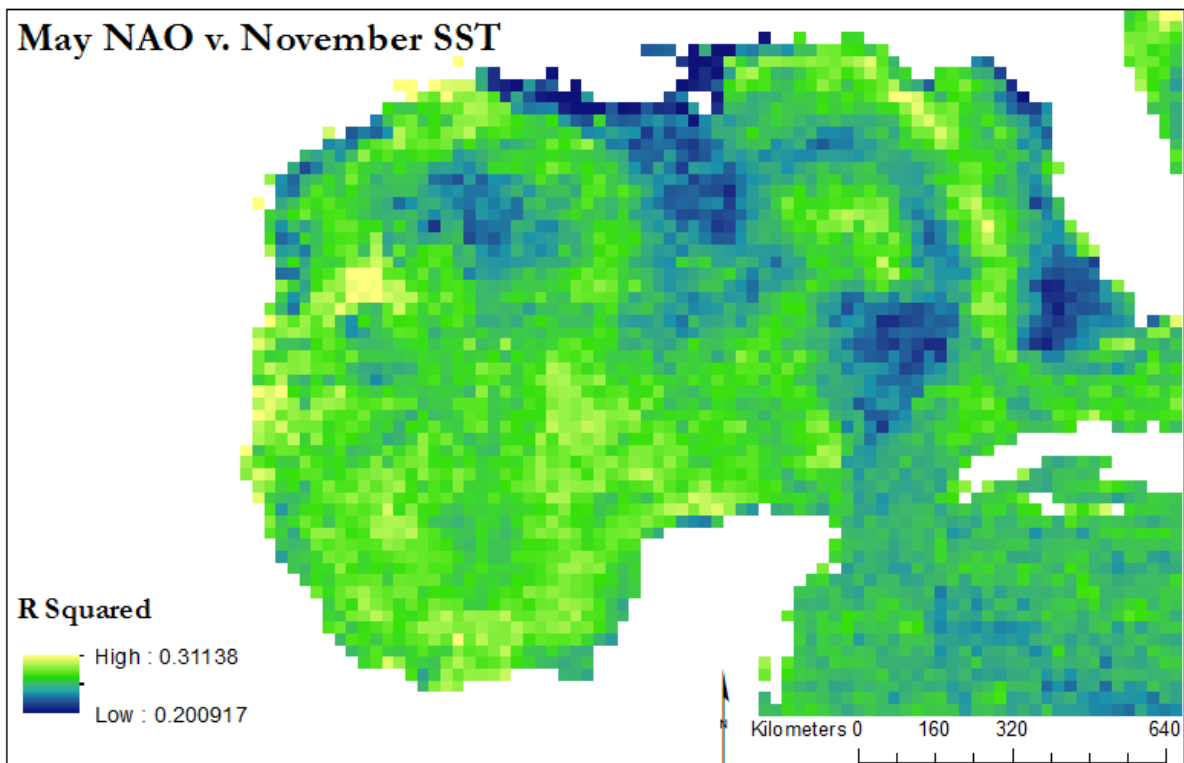


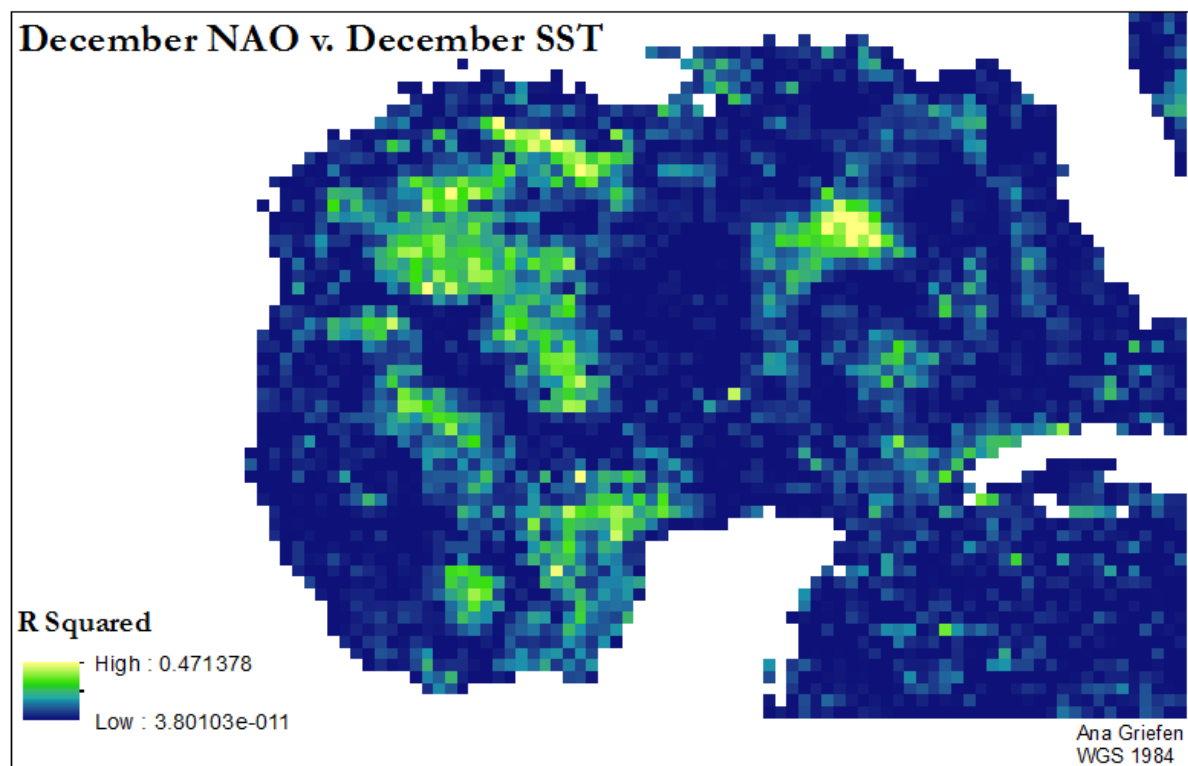
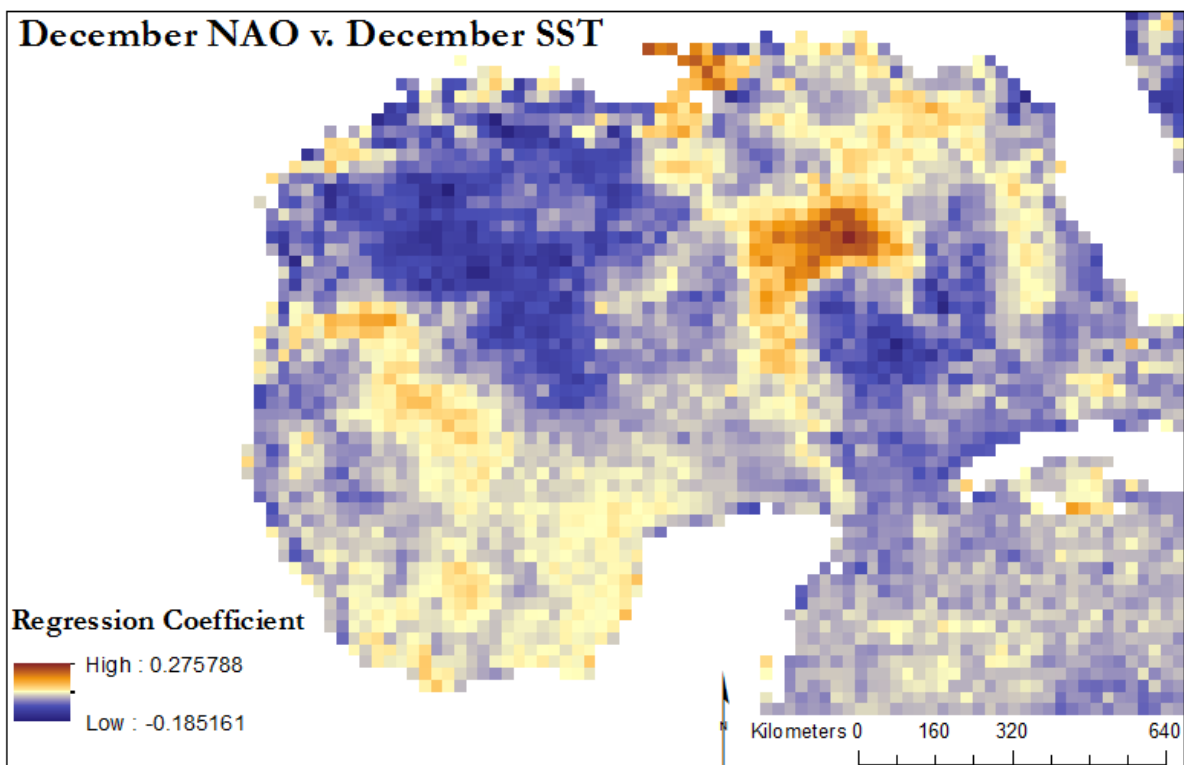


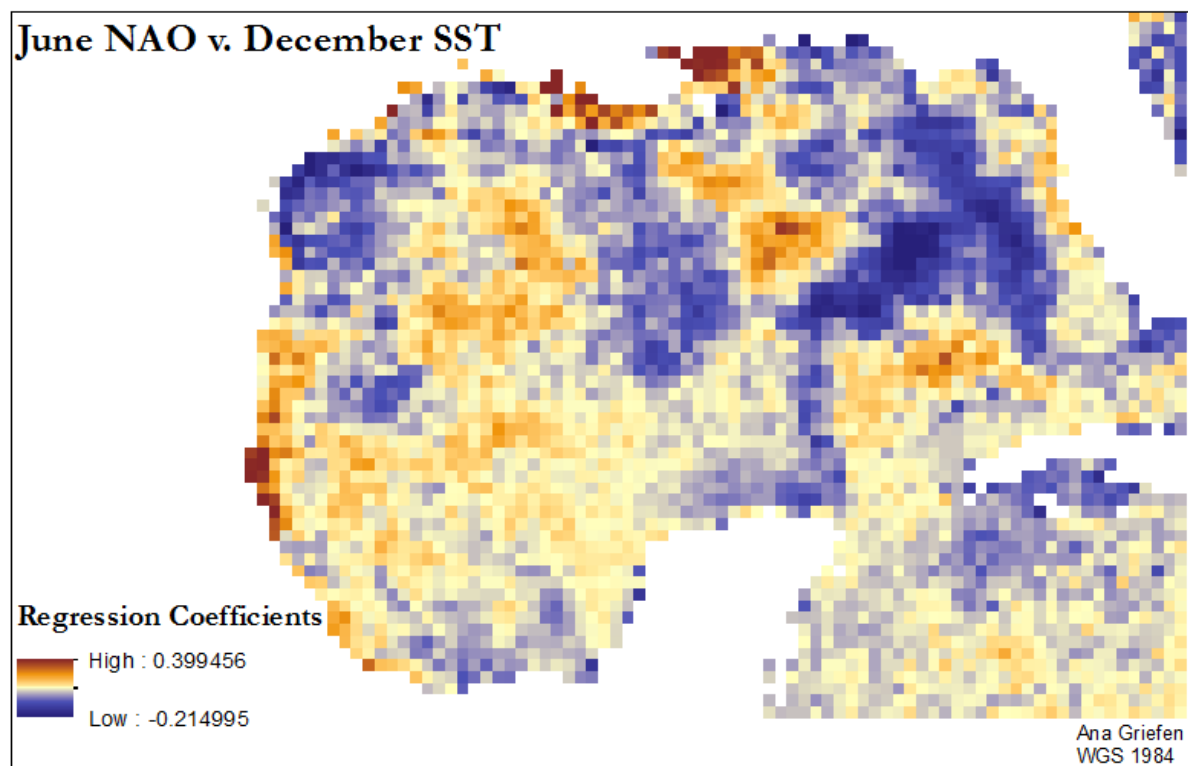
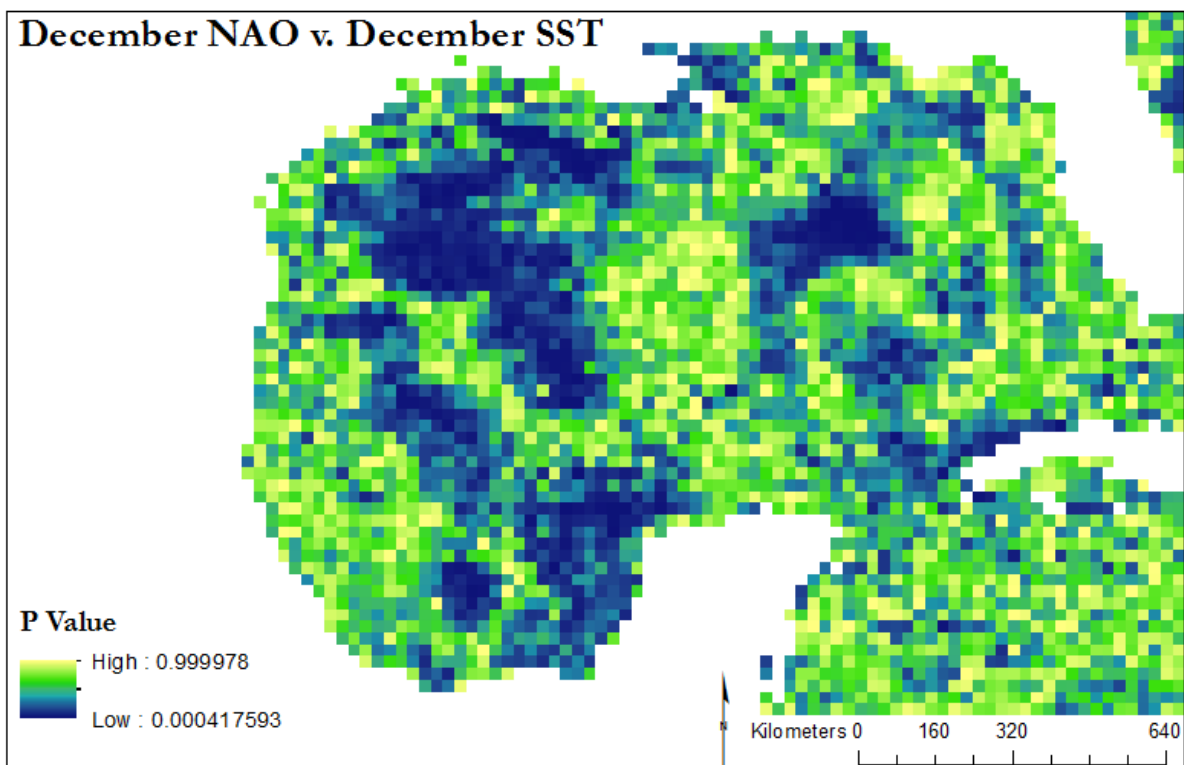


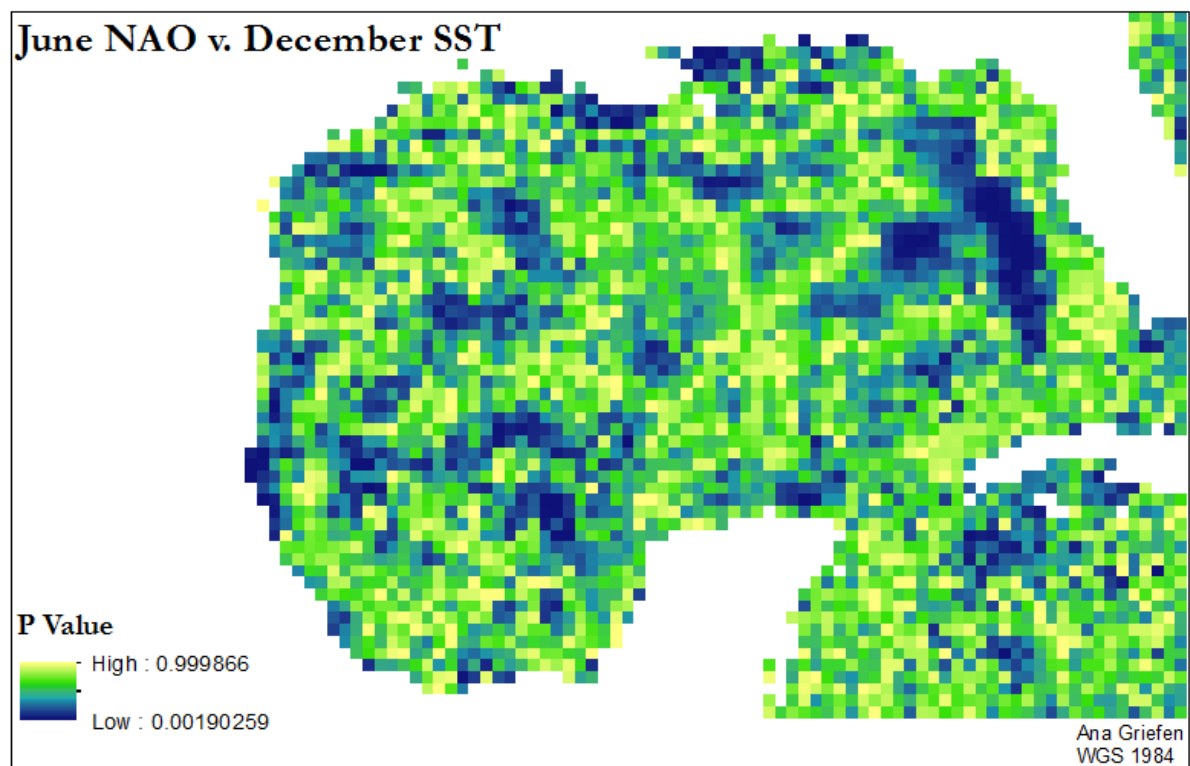
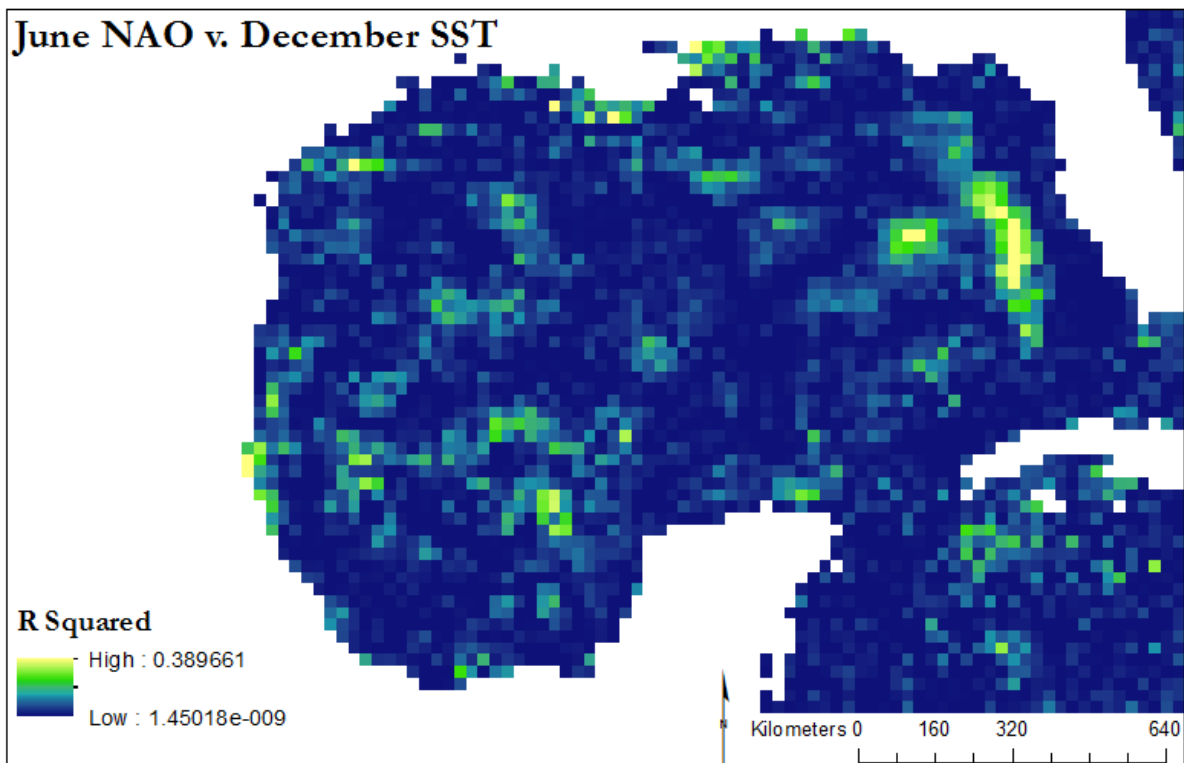












## Appendix B – R analysis and plots

### R Script for Fisheries Catch Regressions:

```
#set working directory
wd<-"M:/Academic/Collaboration/_AJMP/GOM"
setwd(wd)
getwd()#verify working directory
```

```
#NWAtlantic:
```

```
GSS<-read.csv("GS_sword.csv",header=T)
GST<-read.csv("GS_tuna.csv",header=T)
FL<-read.csv("FlCurrent.csv",header=T)
SS25<-read.csv("south25.csv",header=T)
SN30<-read.csv("north30.csv",header=T)
SB<-read.csv("btw25_30.csv",header=T)
```

```
#Gulf of mexico:
```

```
shelf<-read.csv("shelf.csv",header=T)
west<-read.csv("west.csv",header=T)
#check header
#head(GSS)
```

```
#linear regressions by species:
```

```
#NW Atlantic:
```

```
GSW<-lm(Swordfish~NAO,GSS)
GSTu<-lm(Tuna~NAO,GST)
FLS<-lm(Swordfish~NAO,FL)
FLT<-lm(Tuna~NAO,FL)
SS25S<-lm(Swordfish~NAO,SS25)
SS25T<-lm(Tuna~NAO,SS25)
SN30S<-lm(Swordfish~NAO,SN30)
SN30T<-lm(Tuna~NAO,SN30)
SBS<-lm(Swordfish~NAO,SB)
SBT<-lm(Tuna~NAO,SB)
```

```
#GOM:
```

```
shelfT<-lm(Tuna~NAO,shelf)
westT<-lm(Tuna~NAO,west)
shelfS<-lm(Swordfish~NAO,shelf)
westS<-lm(Swordfish~NAO,west)
```

```
summary(GSW)
summary(GSTu)
summary(FLS)
summary(FLT)
summary(SS25S)
summary(SS25T)
summary(SN30S)
summary(SN30T)
summary(SBS)
summary(SBT)
#GOM:
summary(shelfT)
summary(westT)
summary(shelfS)
summary(westS)
```

```
#plot(GSW)
```

```

par(mfrow=c(2,2))
plot(west$Swordfish~west$NAO, xlab="Monthly NAO Index", ylab="Swordfish Catch", main="Western
Gulf of Mexico")
plot(west$Tuna~west$NAO, xlab="Monthly NAO Index", ylab="Tuna Catch", main="Western Gulf of
Mexico")
plot(shelf$Tuna~shelf$NAO, xlab="Monthly NAO Index", ylab="Tuna Catch", main="West Florida Shelf")
plot(shelf$Swordfish~shelf$NAO, xlab="Monthly NAO Index", ylab="Swordfish Catch", main="West
Florida Shelf")

```

#### R Script for Fisheries Distribution Regressions:

```

#set working directory
wd<-"M:/Academic/Collaboration/_AJMP/GOM"
setwd(wd)
getwd()#verify working directory

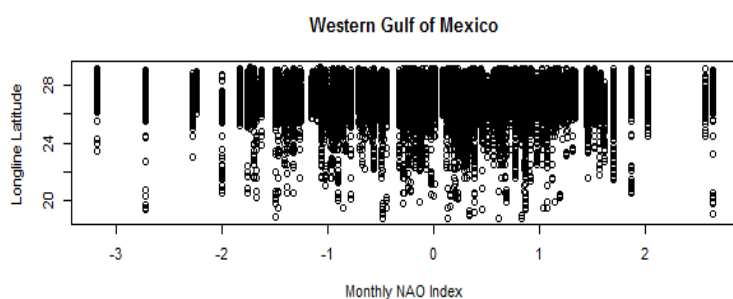
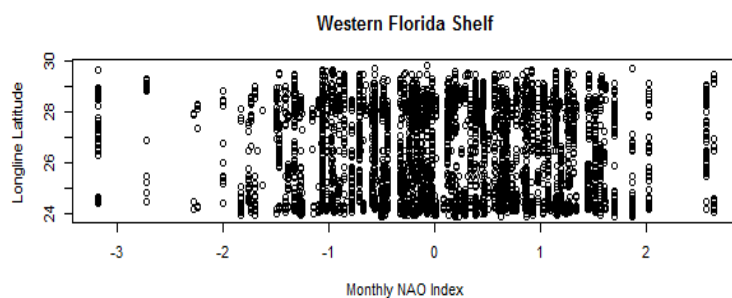
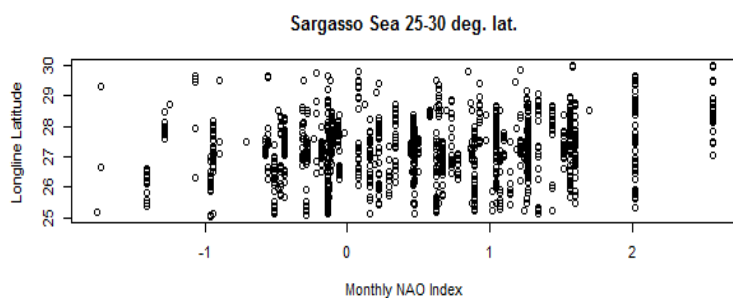
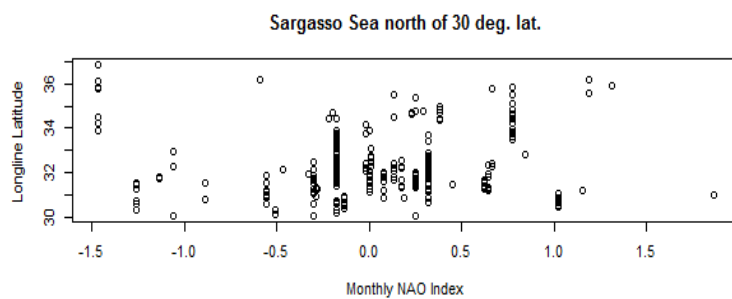
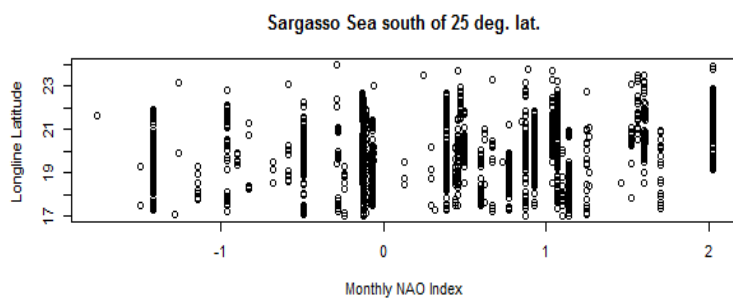
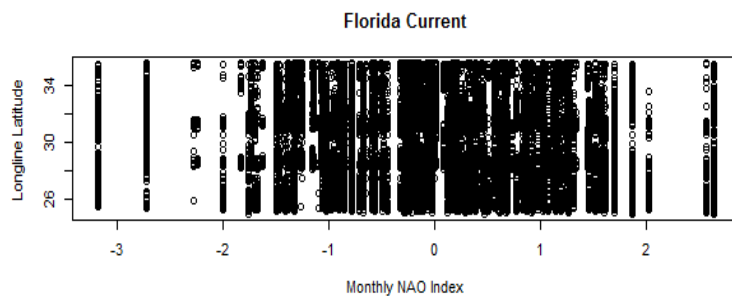
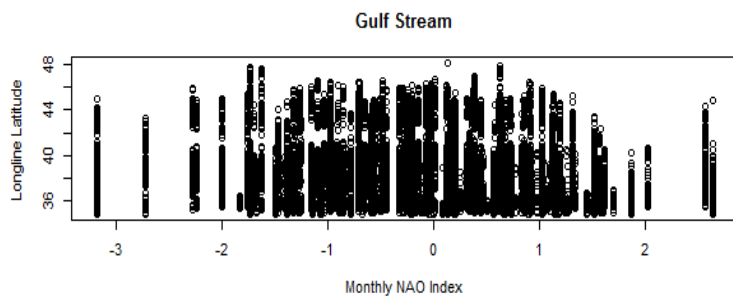
west<-read.csv("west.csv",header=T)
#check header
#head(GS)

#linear regressions by species:
westlat<-lm(LAT~NAO,west)
westlon<-lm(LON~NAO,west)

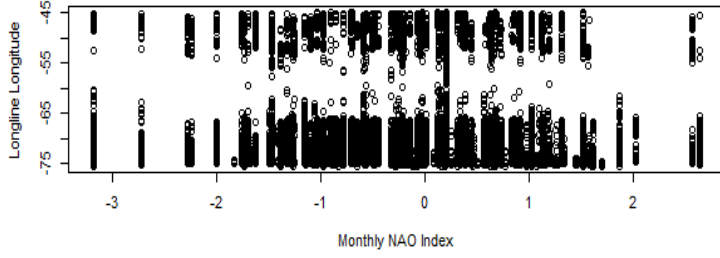
summary(westlat)
summary(westlon)
#plot(GSW)
par(mfrow=c(1,2))
plot(west$LAT~west$NAO, xlab="Monthly NAO Index", ylab="Longline Latitude", main="Western Gulf
of Mexico")
plot(west$LON~west$NAO, xlab="Monthly NAO Index", ylab="Longline Longitude", main="Western
Gulf of Mexico")

```

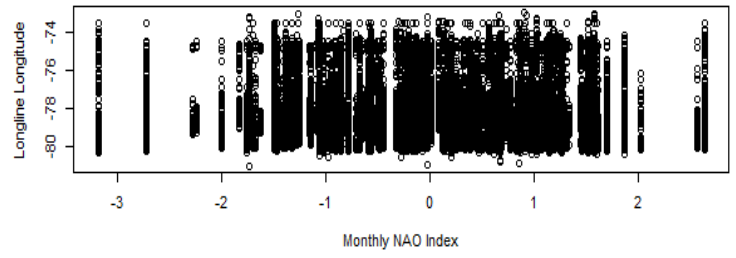




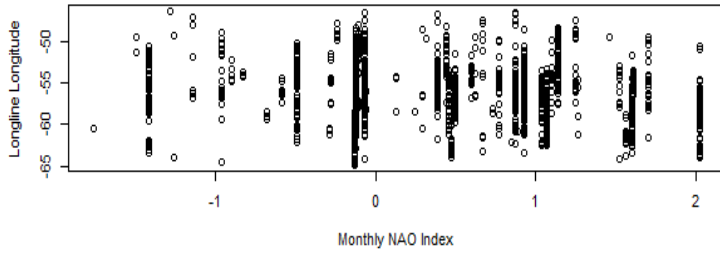
Gulf Stream



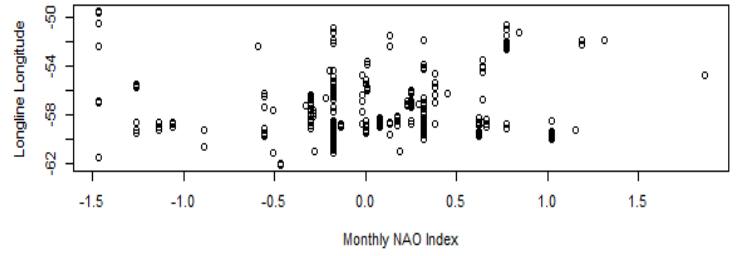
Florida Current



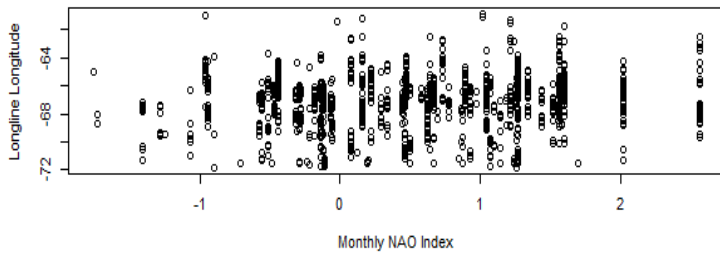
Sargasso Sea south of 25 deg. lat.



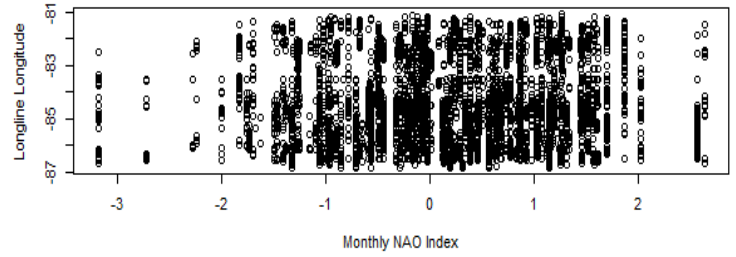
Sargasso Sea north of 30 deg. lat.



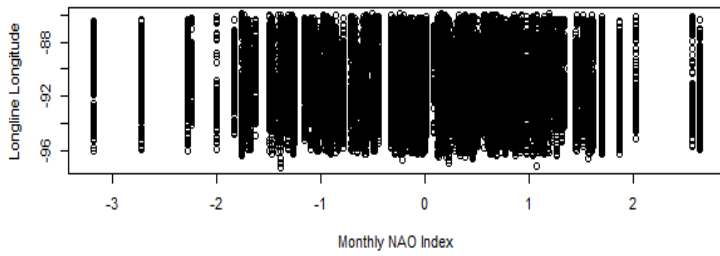
Sargasso Sea 25-30 deg. lat.

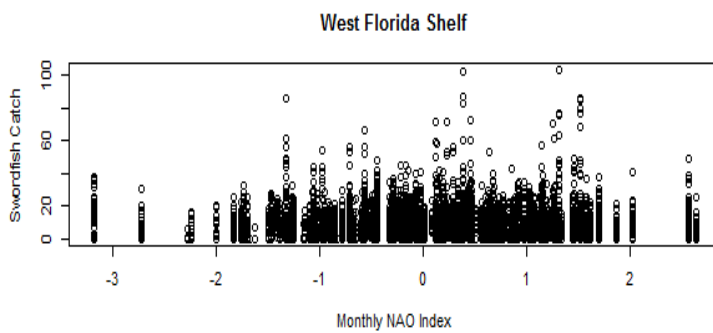
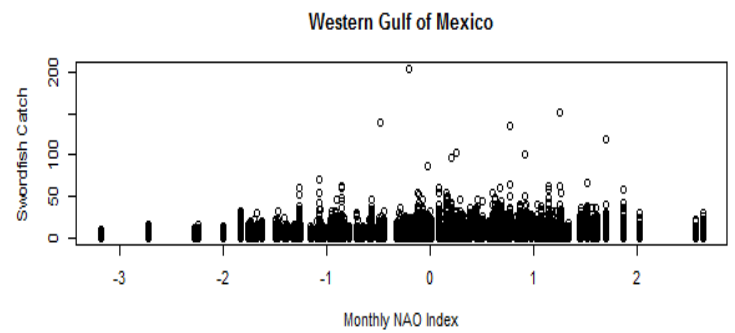
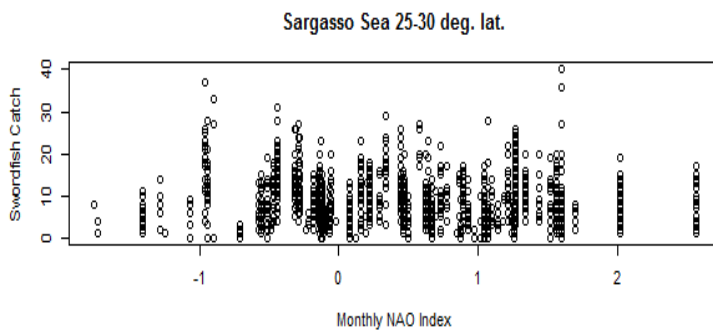
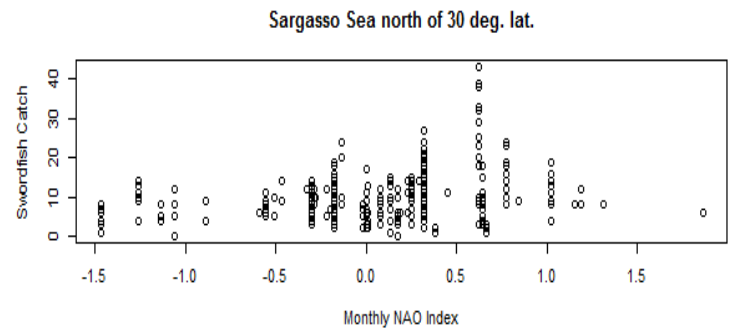
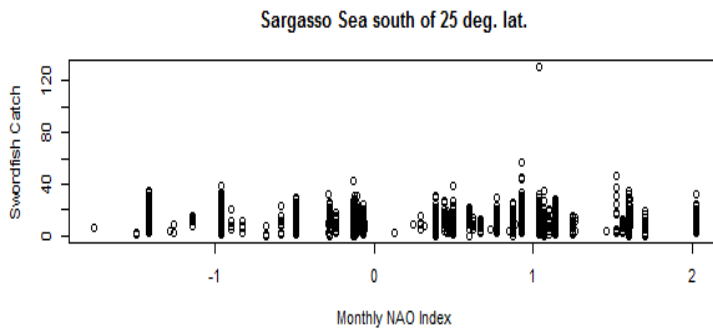
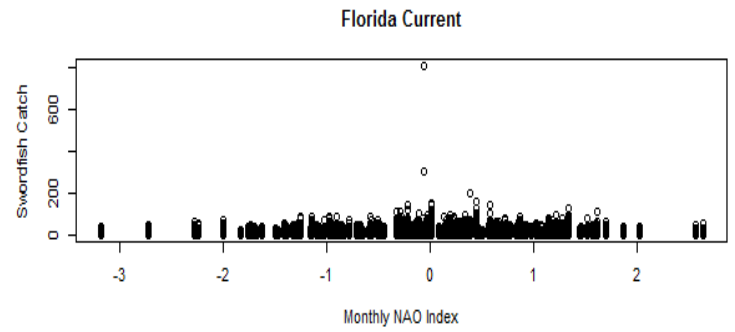
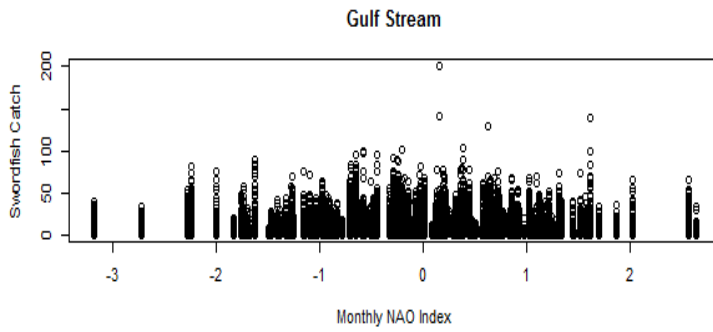


Western Florida Shelf

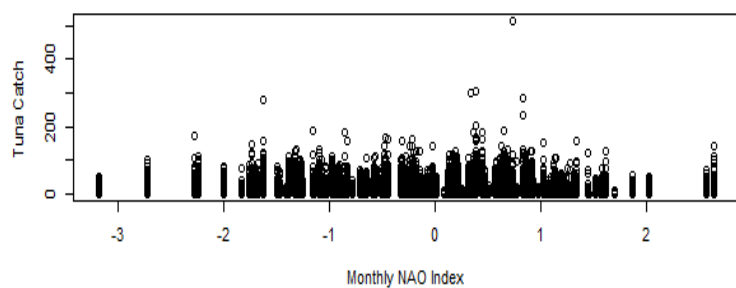


Western Gulf of Mexico

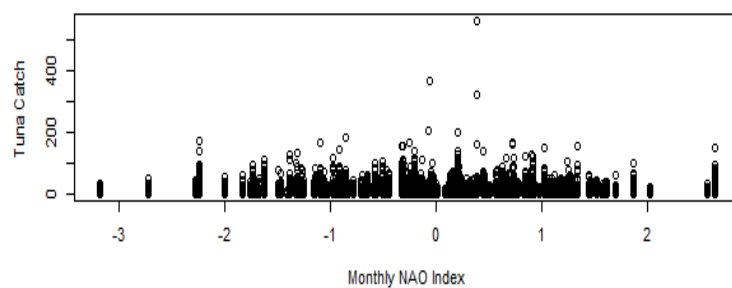




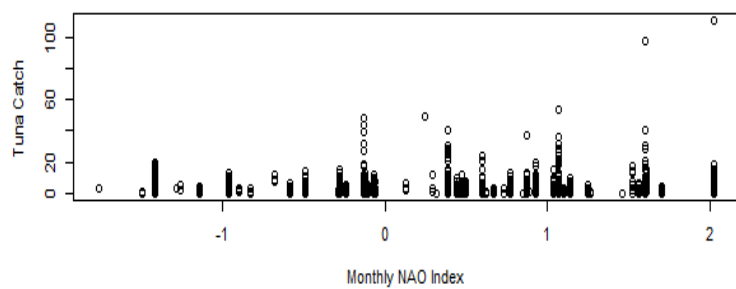
Gulf Stream



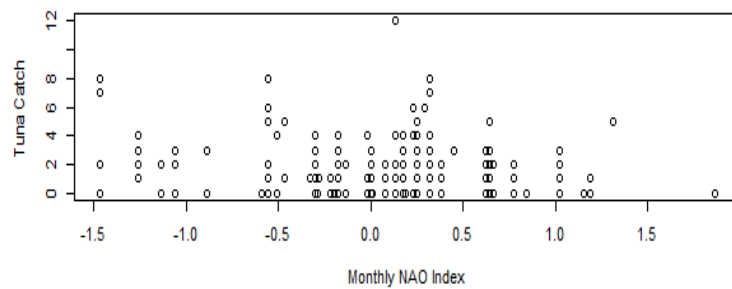
Florida Current



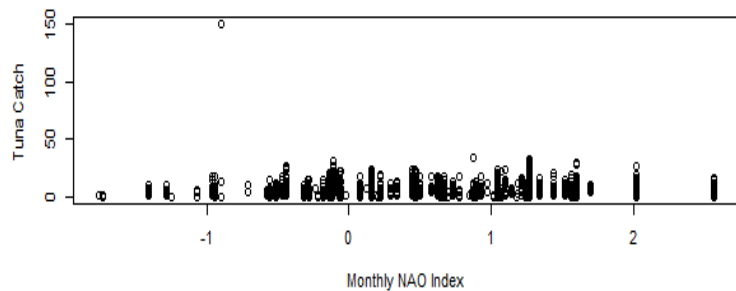
Sargasso Sea south of 25 deg. lat.



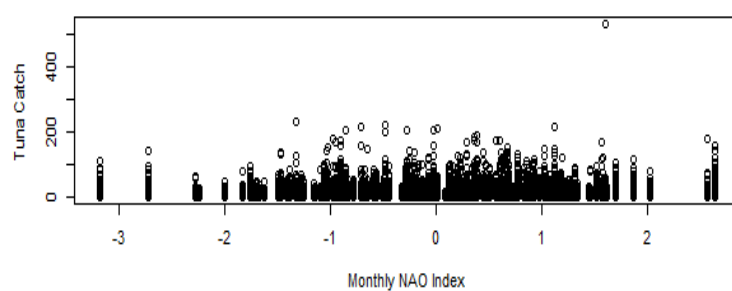
Sargasso Sea north of 30 deg. lat.



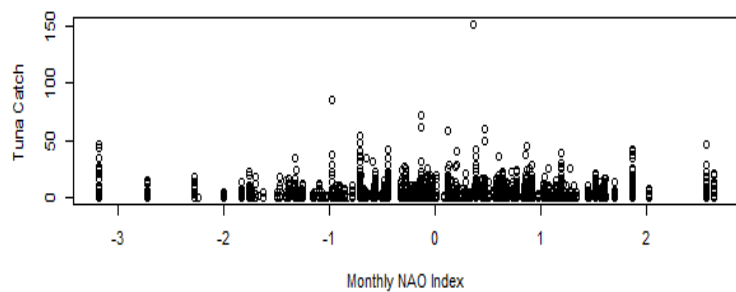
Sargasso Sea 25-30 deg. lat.



Western Gulf of Mexico



West Florida Shelf



## Appendix C – Data preparation in ArcGIS and Python

### C1.Retrieving SST using the Mget tool:

```
# -*- coding: utf-8 -*-
# -----
# ImportSSTrasters.py
# Created on: 2013-12-08 14:49:15.00000
# By: Ana Griefen ENV859
# Description: This script allows the user to download multiple years of monthly
#             rasters from MGET AVHRR Pathfinder SST V5.2 (create climatological rasters)
#             in one run, and organizes the rasters by year into respective folders within
#             the Scratch folder. Dates are specified via user supplied text file.
#             Formatting instructions for this text file are located in the Docs folder.
#             The user must also specify the output workspace (the Scratch folder).
#             Not to be run in ArcMap.
# -----

#Import modules
import arcpy
import arcgisscripting
import os

# Load required toolboxes (for MGET SST)
gp = arcgisscripting.create()
gp.AddToolbox('C:\\Program Files\\GeoEco\\ArcGISToolbox\\Marine Geospatial Ecology Tools.tbx')

#Allow for user input
dates = raw_input("Enter full path of txt file")#user inputs txt file containing specified years
with start and end dates.
fileobj = open(dates,'r')                                #StudyPeriod.txt is located in Data Folder
out_workspace = raw_input("Enter full output path to Scratch") #set output workspace variable
#Prepare for loop
lineStrings = fileobj.readlines()
fileobj.close()

#Loop through each year to download MULTIPLE years of MONTHLY SST data with MGET
for lineString in lineStrings:
    lineData = lineString.split(" ")##split years and dates by space
    year = lineData[0]##designate year (first column in text file)
    Start_date = lineData[1]##designate start date
    End_date = lineData[2]##designate end date
```

```

out_name = "%(ClimatologyBinName)s.img"##set output name variable (month01, month02, etc)
arcpy.CreateFolder_management(out_workspace, year) ##create individual year folders in the
output workspace

output = os.path.join(out_workspace, year) ##join the paths so the output for each year will
go into each respective folder

## Process: Create Climatological Rasters for AVHRR Pathfinder V5.2 SST
gp.AVHRRPathfinderSST52TimeSeriesCreateClimatologicalArcGISRasters_GeoEco("Daily", "Night",
"sea_surface_temperature", "Mean", "Monthly", output, "Add", out_name, "true", "true", "true", "4", "",
"", "", "", "", "1", "1", "", "-100 15 -45 70", Start_date, End_date, "60", "600", "", "true",
"false", "false")

```

## C2. Calculating average SST for all months (Average of all Januaries, average of all Februaries etc)

```

# -*- coding: utf-8 -*-
# -----
# Monthly_mean_cellstats.py
# Created on: 2013-12-08 14:49:15.00000
# By: Ana Griefen ENV859
# Description: This script reads in the rasters downloaded by MGET (specified by
#             user in previous script) and calculates each monthly average across
#             all years that were downloaded. For example, if a user downloads 3 years
#             of monthly rasters, this tool will average the respective months of each
#             of those 3 years, producing an average raster for January, February,
#             March...etc. User specifies workspace (Scratch) and output path (Data).
# -----

# Import arcpy module
import arcpy

# Check out necessary licenses (for cell statistics)
arcpy.CheckOutExtension("spatial")

## Navigation and loop preparation
#set workspace to folder containing rasters
arcpy.env.workspace = raw_input("Set workspace path to Scratch")#needs full path
"M:\Academic\Collaboration\AJMP\GIS\rawSSTdata"
#create list of year folders within the Scratch folder -- this makes the script dependent on the
prior script; it will only average data (years) found in the scratch folder.
workspaces = arcpy.ListWorkspaces("?", "ALL")
print workspaces

#create empty lists to contain monthly rasters from each year (month lists)
janList = []
febList = []
marchList = []
aprilList = []
mayList = []
juneList = []
julyList = []
augList = []
septList = []
octList = []
novList = []
decList = []

## Loop through year folders and append monthly rasters to month lists
for workspace in workspaces:
    path1 = workspace + "\\month01.img;"#create variable path names for each monthly raster of
each year
    janList.append(path1)#append each year's month to month list
    path2 = workspace + "\\month02.img;"
    febList.append(path2)
    path3 = workspace + "\\month03.img;"
    marchList.append(path3)
    path4 = workspace + "\\month04.img;"
    aprilList.append(path4)

```

```

path5 = workspace + "\\month05.img;"
mayList.append(path5)
path6 = workspace + "\\month06.img;"
juneList.append(path6)
path7 = workspace + "\\month07.img;"
julyList.append(path7)
path8 = workspace + "\\month08.img;"
augList.append(path8)
path9 = workspace + "\\month09.img;"
septList.append(path9)
path10 = workspace + "\\month10.img;"
octList.append(path10)
path11 = workspace + "\\month11.img;"
novList.append(path11)
path12 = workspace + "\\month12.img;"
decList.append(path12)

##Prepare input rasters for cell statistics (lists to strings)
inputJan = ''.join(janList)#remove commas and 's and convert path list to one string
inputJan2 = inputJan.strip(';')#remove last ;
inputFeb = ''.join(febList) #repeat for each month
inputFeb2 = inputFeb.strip(';')
inputMarch = ''.join(marchList)
inputMarch2 = inputMarch.strip(';')
inputApril = ''.join(aprilList)
inputApril2 = inputApril.strip(';')
inputMay = ''.join(mayList)
inputMay2 = inputMay.strip(';')
inputJune = ''.join(juneList)
inputJune2 = inputJune.strip(';')
inputJuly = ''.join(julyList)
inputJuly2 = inputJuly.strip(';')
inputAug = ''.join(augList)
inputAug2 = inputAug.strip(';')
inputSept = ''.join(septList)
inputSept2 = inputSept.strip(';')
inputOct = ''.join(octList)
inputOct2 = inputOct.strip(';')
inputNov = ''.join(novList)
inputNov2 = inputNov.strip(';')
inputDec = ''.join(decList)
inputDec2 = inputDec.strip(';')

##Prepare output paths for cell statistics
#set output paths for each month
output = raw_input("Set output path to Data folder")#needs full path
"M://Academic//Collaboration//_AJMP//GIS//FORALLYEARS//AVGofAllYrs"
January = output + "\\January"
February = output + "\\February"
March = output + "\\March"
April = output + "\\April"
May = output + "\\May"
June = output + "\\June"
July = output + "\\July"
August = output + "\\August"
September = output + "\\September"
October = output + "\\October"
November = output + "\\November"
December = output + "\\December"

##Calculate monthly average rasters using cell statistics
#"DATA" indicates 'no data' cells are ignored
arcpy.gp.CellStatistics_sa(inputJan2, January, "MEAN", "DATA")
arcpy.gp.CellStatistics_sa(inputFeb2, February, "MEAN", "DATA")
arcpy.gp.CellStatistics_sa(inputMarch2, March, "MEAN", "DATA")
arcpy.gp.CellStatistics_sa(inputApril2, April, "MEAN", "DATA")
arcpy.gp.CellStatistics_sa(inputMay2, May, "MEAN", "DATA")
arcpy.gp.CellStatistics_sa(inputJune2, June, "MEAN", "DATA")
arcpy.gp.CellStatistics_sa(inputJuly2, July, "MEAN", "DATA")
arcpy.gp.CellStatistics_sa(inputAug2, August, "MEAN", "DATA")
arcpy.gp.CellStatistics_sa(inputSept2, September, "MEAN", "DATA")
arcpy.gp.CellStatistics_sa(inputOct2, October, "MEAN", "DATA")
arcpy.gp.CellStatistics_sa(inputNov2, November, "MEAN", "DATA")
arcpy.gp.CellStatistics_sa(inputDec2, December, "MEAN", "DATA")

```

### C3. Converting SST to points for interpolation, to remove “nodata” holes.

```
# -*- coding: utf-8 -*-
# -----
# Raster2point.py
# Created on: 2014-03-12 16:47:31.00000
# (generated by ArcGIS/ModelBuilder)
# Description:
# -----

# Import arcpy module
import arcpy
import os

# Check out any necessary licenses
arcpy.CheckOutExtension("spatial")

#arcpy workspace
path = "M:\\Academic\\Collaboration\\_AJMP\\GIS\\FORALLYEARS\\Zscore_differences"

#Folders
Workspaces = os.listdir(path)

print Workspaces

for folders in Workspaces:
    raw = folders[-7:]
    part = "M:\\Academic\\Collaboration\\_AJMP\\GIS\\FORALLYEARS\\Z_DiffPoint"
    Output = part + "\\\" + raw + ".Dpt"
    Input = path + "\\\" + raw
    # Process: Raster to Point
    arcpy.RasterToPoint_conversion(Input, Output, "Value")
```

#### C4. Interpolating SST, to remove “no data” holes.

```
# -*- coding: utf-8 -*-
# -----
# Interpolate.py
# Created on: 2014-04-07 11:01:25.00000
# (generated by ArcGIS/ModelBuilder)
# Description:
# -----

# Import arcpy module
import arcpy
import os

# Check out any necessary licenses
arcpy.CheckOutExtension("GeoStats")

# Set Geoprocessing environments
arcpy.env.scratchworkspace = "C:\\Users\\jmb122\\Documents\\ArcGIS\\Default.gdb"
arcpy.env.mask = "M:\\Academic\\Collaboration\\_AJMP\\GIS\\FORALLYEARS\\Scratch\\mask3.shp"
arcpy.env.workspace = "M:\\Academic\\Collaboration\\_AJMP\\GIS\\SSTPoints"

#arcpy workspace
path = "M:\\Academic\\Collaboration\\_AJMP\\GIS\\SSTPoints"

#Folders
Workspaces = os.listdir(path)

print Workspaces

for folders in Workspaces:
    end = folders [-3:]
    if end == ".shp":
        Input = path + "\\\" + folders
        name = folders[:11]
        Output = "M:\\Academic\\Collaboration\\_AJMP\\GIS\\SST_IDW\\\" + name + ".img"
        Output_geostatistical_layer = ""
        arcpy.IDW_ga(Input, "GRID_CODE", Output_geostatistical_layer, Output,
"0.219833333333334", "2", "NBRTYPE=Standard S_MAJOR=19.4307050913554 S_MINOR=19.4307050913554
ANGLE=0 NBR_MAX=15 NBR_MIN=10 SECTOR_TYPE=ONE_SECTOR", "")
        print "finished" + name
    else:
        print "nope"
```



## C5. After interpolating, clipping study area into smaller areas (FAO areas 21 and 31 as well as the Gulf. This study only included the Gulf due to time constraints)

```
# Clip31.py
# Created on: 2014-03-25 13:19:37.00000
# (generated by ArcGIS/ModelBuilder)
# Description:
# -----

# Import arcpy module
import arcpy
import os
# Check out any necessary licenses
arcpy.CheckOutExtension("spatial")
#arcpy workspace
path = "M:\Academic\Collaboration\_AJMP\GIS\SST_IDW"

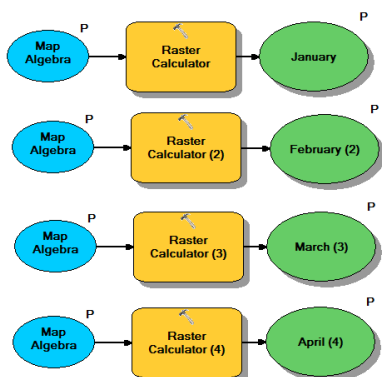
#Folders
workspaces = os.listdir(path)

print workspaces

for rasters in workspaces:
    if rasters[-3:] == ".img":
        print rasters
        Input = path + "\\" + rasters
        outputpath1 =
        "M:\\Academic\\Collaboration\\_AJMP\\GIS\\FAO_Regions\\Individualmonths&years\\Area31"
        outputpath2 =
        "M:\\Academic\\Collaboration\\_AJMP\\GIS\\FAO_Regions\\Individualmonths&years\\Area21"
        outputpath3 =
        "M:\\Academic\\Collaboration\\_AJMP\\GIS\\FAO_Regions\\Individualmonths&years\\Gulf"
        Output1 = outputpath1 + "\\S" + rasters
        Output2 = outputpath2 + "\\N" + rasters
        Output3 = outputpath3 + "\\G" + rasters
        print Output2
        print Input
        # Process: Clip
        arcpy.Clip_management(Input, "-100 15 -45 35", Output1, "", "", "NONE",
        "NO_MAINTAIN_EXTENT")
        arcpy.Clip_management(Input, "-100 35 -45 70", Output2, "", "", "NONE",
        "NO_MAINTAIN_EXTENT")
        arcpy.Clip_management(Input, "-97.867089 17.896628 -80.479961 30.769661", Output3, "",
        "", "NONE", "NO_MAINTAIN_EXTENT")

print "finished!!"
```

## C6. Calculating the Z score for every month, as well as the average-month dataset (all Januaries, all Februaries, etc)



Model shown here abbreviated for the sake of clarity. Calculations in the Raster Calculator were: (Raster - average cell value of raster) / standard deviation of raster

## C7. Calculating the difference between the Z score of each individual month, and the Z score of the average month (Ex. Average across all Januaries - January 1989)

```

# minus.py
# Created on: 2014-04-08 14:48:48.00000
# (generated by ArcGIS/ModelBuilder)
# Description:
# -----
# Import arcpy module
import arcpy
import os
# Check out any necessary licenses
arcpy.CheckOutExtension("spatial")
#arcpy workspace
path = "M:\\Academic\\Collaboration\\_AJMP\\GIS\\Zscore_IDW"

#Folders
workspaces = os.listdir(path)

#print Workspaces

for rasters in workspaces:
    if rasters[:3] == "aug":
        if rasters[-3:] == ".xml":
            print "yikes!"
        else:
            print rasters
            Input = "M:\\Academic\\Collaboration\\_AJMP\\GIS\\Zscore_IDW\\" + rasters
            output = "M:\\Academic\\Collaboration\\_AJMP\\GIS\\Zscore_diffs\\" + rasters
            Month = "M:\\Academic\\Collaboration\\_AJMP\\GIS\\ZscoreDiffAverage\\august"
            arcpy.gp.Minus_sa(Month, Input, output) # Process: Minus
    else:
        print "no"

print "finished!"

```